Consumer and brand engagement on Facebook brand pages

Chedia Dhaoui

This thesis is presented for the degree of

Doctor of Philosophy

Faculty of Business and Economics, Department of Marketing and Management

Macquarie University, Sydney

11th March 2018

Table of contents

Thesis Summary

Social media has sparked a remarkable change in the way brands engage with consumers and has empowered consumers to collectively voice their opinions with unprecedented scale. Challenged by the empowerment that consumers have gained, marketers are continuously engaging consumers through dedicated brand communities on social media platforms. Facebook brand pages are widely used by brands to engage with consumers because they support multi-way interactions between brands and consumers and among consumers themselves. These interactive experiences are what marketers call consumer brand engagement, a concept with much debate as to its scope and dimensions, but less attention is given to decipher the intricacies between brand engagement and consumer engagement behaviors, to understand its emotional dynamics, and to examine the role of webcare strategies to manage consumer conversations on Facbook brand pages. To fill those gaps, this thesis contains three co-authored papers. The first paper is an empirical analysis of the interplay between brand engagement and consumer engagement behaviors as well as among consumers themselves on Facebook brand pages. The paper develops a conceptual model of engagement behaviors, translates its components into measurable constructs and empirically investigates the effects of brand engagement on consumer engagement and among consumers in 2,740 Facebook brand pages. The second paper examines the impact of 64,347 webcare interventions embedded within 24,557 consumer conversations on Facebook brand Pages to determine whether type (proactive versus of reactive), voice (personal versus impersonal), timing (early versus late) and number (single versus multiple) of webcare interventions influence the volume and valence of consumer conversations. The third paper tackles the emotional perspective of consumer brand engagement. Drawing on emotional branding and contagion research, the paper examines the dynamics of emotional brand content and consumer reactions in 942 Facebook brand pages.

Statement of Original Authorship

The work embodied in this thesis has not been submitted for a higher degree to any other university or institution. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made.

Chedia Dhaoui

(43718353)

11th March 2018 Signed

Acknowledgements

I would like to acknowledge the contribution of my main supervisor and co-supervisor in each of the studies and subsequent papers. While I am the principal author for all of the studies and papers, I have been assisted in the writing of the papers by Associate Professor Cynthia M. Webster and Senior Lecturer LayPeng Tan. The contribution ratio of authors is outlined below.

- Brand and Consumer Engagement Behaviors on Facebook Brand Pages: Alternative Measurements and Contributing Factors

  Chedia Dhaoui (70%), Cynthia M. Webster (30%)

- Webcare Interventions in Consumer-to-Consumer Conversations: An Empirical Investigation on Facebook Brand Pages

  Chedia Dhaoui (70%), Cynthia M. Webster (15%), LayPeng Tan (15%)

- Emotional Dynamics on Facebook Brand Pages

  Chedia Dhaoui (70%), Cynthia M. Webster (15%), LayPeng Tan (15%)

I would like to thank the anonymous reviewers from the Journal of Interactive Marketing, the journal of Marketing Management, the 39th Annual ISMS Marketing Science Conference (2017), the Winter AMA Conference (2017), the Australian and New Zealand Marketing Academy Conference (ANZMAC) 2016 and the 6th Global Innovation and Knowledge Academy (GIKA) (2016).

Personal Acknowledgements

There are no words that can express my sincere gratitude to my principal supervisor, Associate Professor Cynthia Webster, for her continuous encouragement, invaluable guidance and expertise to achieve this work. Thank you very much for your enthusiasm, advice and kindness that made me feel very lucky to do research under your supervision. To me you are an inspiration in life and work.

I would like to express my deepest gratitude to my associate supervisor Dr LayPeng Tang, for her generous contribution to make this work possible. I am very thankful to you for your time devoted to enrich my research with valuable comments and being very supportive of me throughout this thesis.

My gratitude to my kindhearted husband Adnene for his support and patience. Thank you very much for your help to take care of the kids when I am busy with deadlines.

I wish to express my love to my special boy Danny for his effort to help me with his quietness, his kindness and for always encouraging me with his beautiful words: “mummy never give up! Believe in yourself!”

My love goes also to my precious daughter Dana who makes me happy every day, despite the stress of work, you enlighten my days with your beautiful smiles and you give me lots of hope that tomorrow will be better than today!

Without you, this work would not have been possible, I am very thankful to all of you.

Chapter 1: Introduction to the thesis

In today's digital era, brand managers are striving to keep pace with the dramatic changes in the digital marketing landscape to stay ahead of the competition. They have embraced social media as a potent interactive marketing channel to communicate with empowered consumers. As of the last quarter of 2016, over 60 million businesses have created Facebook brand pages to engage with consumers, up by more than 20 million new businesses since the year before. This remarkable growth is further highlighted by up to 32% of Facebook users following their favorite brands on Facebook (Sensis, 2015). Given the massive number of active Facebook users (reaching 1.4 billion daily users as of Q4, 2017 (Facebook, 2018)), ubiquitously connected via mobile phones, we are witnessing the crucial role played by Facebook as an interactive platform serving both marketers and consumers.

Consumers are now empowered by their online connections to other consumers (Lamberton and Stephen, 2016) as they co-create and disseminate brand related content to a broader brand community. The proliferation of social networks has enabled brands to connect and communicate with consumers in an interactive way (Sasser et al. 2014). For instance, interactions on Facebook are not restricted to one-to-one dialogues between brands and consumers, instead consumers engage in many-to-many interactions with the brand and with other consumers (Meng et al., 2016; Choudhury and Harrigan 2014). These interactive experiences between brands and consumers, as well as among consumers are what marketing researchers describe as consumer brand engagement (Hollebeek, Glynn and Brodie, 2014), a concept with much debate as to its scope, dimensions, and the most effective evaluation method to adopt (Richter, Riemer and vom Brocke, 2011).

Much of the consumer brand engagement academic research is conceptual in nature, differentiating between the cognitive, emotional and behavioral dimensions of consumer brand engagement (Hollebeek, Glynn and Brodie, 2014; Dessart, Veloutsou and Morgan-Thomas, 2016). Most studies focus on consumer engagement, leaving relatively unexplored the intricacies between brand engagement and consumer engagement. The practitioner-oriented view of consumer brand engagement also suffers important gaps as it primarily explores the behavioral manifestations of engagement (e.g. Schivinski, Christodoulides and Dabrowski, 2016; Jaakkola and Alexander, 2014), yet failing to consider its emotional dynamics. Although many researchers (e.g. Hollebeek, Glynn and Brodie 2014; Dessart, Veloutsou and Morgan-Thomas, 2016) have considered emotional engagement as one of the components of consumer and brand engagement, they do not examine its dynamics in actual consumer brand engagement. Furthermore, emotional branding on social media is often considered as a way for brands to spread emotionally loaded content and influence consumers, whereas brands can also use emotional branding to respond to emotionally loaded consumer generated content in either situations of consumer complaint about the brand or consumer praise of the brand. However, very little research has explored the webcare strategies that brands deploy to manage consumer conversations on social media platforms and the emotional dynamics that occur in such situations.

This thesis examines consumer brand engagement on Facebook brand pages with greater attention given to the intricacies between consumer engagement behaviors and brand engagement behaviors, especially given the direct linkage with brand strategy and their importance for managerial action (Bolton 2011). The overall aim is also to empirically explore the behavioral and emotional dimensions of consumer brand engagement on a major social media platform like Facebook. As an introduction, the remainder of this chapter broadly examines consumer and brand engagement from both conceptual and practical perspectives, sheds light on important gaps within the literature, and provides justification of the significance of the research. Research problems and specific objectives of the research are then outlined. Finally, this chapter concludes with a summary of the subsequent chapters in the thesis.

Background to the Research

Conceptually, consumer and brand engagement fall within the theoretical perspectives of social exchange theory (Blau 1964), service-dominant logic (Vargo and Lusch 2004, 2008; Karpen et al. 2012) and relationship marketing theory (Vivek et al. 2012; Ashley et al. 2011). Emerging as a highly influential concept in contemporary marketing (Precourt, 2016), consumer brand engagement is still at an early stage of understanding (France et al. 2016) offering a multiplicity of engagement-based concepts (Brodie et al., 2011; Dessart, Veloutsou and Morgan-Thomas, 2016) and definitions (Leckie, Nyadzayo and Johnson, 2016). Nevertheless, most researchers agree with Brodie et al. (2011, p. 259) that “specific interactive experiences are an indispensable component of a customer’s particular engaged state” and that these interactions take place between a specific “engagement subject” (e.g. consumer) and “engagement object” (e.g. brand). Yet, this definition is still confined to the traditional one-way business-to-consumers conceptualization of engagement.

The considerable advancements of social media during the last decade have revolutionized not only the way brands engage with their consumers, but also the roles of consumers in the engagement process. In a sense, social media gives consumers the same, if not more voice than brands, disrupting consumer-brand relationships and creating new challenges for marketers (Constantinides, Romero, and Boria, 2009). Brand managers can no longer afford to ignore their consumers’ important online voice (Gensler et al., 2013). They are also offered new opportunities to interact in a more conversational way with consumers and tap into the unfettered consumer generated content readily available on social media platforms. With digital marketing now treated as a “many-to-many conversation” between businesses and consumers as well as among consumers themselves (Lusch et al., 2010; Sasser et al. 2014), conceptual clarification and a more comprehensive approach to consumer brand engagement is needed. The following section provides definitions and highlights points of differentiation for key engagement concepts.

Definition and Differentiation of Key Concepts

Much of previous research on consumer and brand engagement recognizes the multi-dimensional nature of engagement distinguishing one or many of its cognitive, emotional and behavioral dimensions (Brodie et al, 2013; Hollebeek, Glynn and Brodie 2014; Dessart, Veloutsou and Morgan-Thomas, 2016). This thesis adopts such a multi-dimensional view of engagement, focusing mainly on the behavioural and emotional components of engagement. To fully capture engagement on FBPs, this thesis examines the interactions occurring between consumers and the brand, as well as among consumers themselves. This approach allows for further understanding and fosters the potential synergies between consumer engagement (CE) and brand engagement (BE), and in combination consumer brand engagement (CBE). This section defines, differentuiatiates and operationalizes key concepts in the particular context of FBPs.

Engagement

The term "engagement" has been extensively discussed in the literature across different academic disciplines, including psychology, sociology and social science (Brodie et al., 2011). In the marketing field, there is a relatively recent academic debate around the concept "engagement" (Hollebeek, Glynn and Brodie, 2014). Among others, Higgins and Scholer (2009) define engagement as "a state of being involved, occupied, fully absorbed or engrossed in something – sustained attention" (p.102).

This indicates that being engaged is motivationally driven and can be "inferred from a pattern of action or withdrawal with respect to a target object" (Pham and Avnet, 2009, p.116). Skinner et al. (2009) claim that engagement is, at its core, the "manifestation of an ongoing motivated action" (p.8). As pointed out by Drejing, Thill and Hemeren (2015), actions have the properties of being goal -directed, sustained and energized, which in turn reveal the motivational driver of engagement. Furthermore, the level of motivation drives the intensity of engagement (Brehm and Self, 1989). For example, highly engaged consumers are those who are highly motivated to engage with the brand and/or with other consumers and weakly engaged consumers are those who lack motivation.

Furthermore, consumer engagement contributes to value co-creation (Brodie et al, 2011; Jaakkola and Alexander, 2014). The co-creation of value occurs when consumers invest resources (e.g. knowledge, experience, time) to augment or co-develop the brand’s offering, and influence or mobilize other consumers’ actions toward the brand (Jaakkola and Alexander, 2014). For example, brand advocates can influence other consumers by sharing their positive experiences with the brand, spreading positive word-of-mouth and recommending the brand. Consumers can also suggest new ideas and participate in product co-development. Yet, co-creation can also take a negative turn consisting, for example, of influencing other consumers to boycott the brand.

This thesis builds on, and extends prior definitions and considers engagement as a set of activities initiated and performed by the brand and/or consumers in their dynamic interactions on Facebook brand pages (FBPs). FBPs facilitate engagement because they enable consumers and brand fans to voluntarily join and engage with the brand and with other consumers. As this thesis focuses on engagement behaviours, it is necessary to distinguish between engagement and interactivity.

Differences between engagement and interactivity

While most researchers agree that engagement is an interactive experience (Jaakkola and Alexander, 2014), the concepts of engagement and interactivity are in fact distinct but closely related to each other. Engagement occurs through brand-consumer and consumer-consumer interactions. We consider that without interactivity, engagement cannot be achieved. In contrast to engagement, interactivity does not presume a motivational driver.

Interactivity is commonly defined as "the degree to which two or more communication parties can act on each other, on the communication medium and on the messages and the degree to which such influences are synchronized" (Liu and Shrum, 2002, p.54). Three dimensions of interactivity have been discussed in the literature: active control, two-way communication and synchronicity (Liu and Shrum, 2002). First, the active control dimension of interactivity refers to the ability of brands and consumers to voluntarily influence their experiences. This dimension fits well with the spontaneous and unrestricted nature of consumer engagement through voluntary resource investments in brand interactions (Hollebeek, Srivastava and Chen, 2016). Second, the two-way communication characterizing interactivity reflects reciprocal exchange of information between parties. This thesis examines the interactions occurring between brands and consumers and among consumers on FBPs. This corresponds to the two-way communication aspect of engagement. In particular, FBPs facilitate the occurrence of a multidirectional communication (many-to-many) between the brand and consumers, and among consumers as well. To be engaged, consumers respond to brand actions (i.e., brand posts) or to other consumers' actions (i.e., consumer comments). Third, the synchronicity dimension of interactivity refers to the speed of interactions operating between the communicating parties. In this thesis, the promptness of brand actions (also referred to as webcare interventions in Chapter 3) is examined as the speed by which the brand responds to consumer comments, which is along the same lines as the synchronicity of interactivity.

Consumer Engagement

Consumer engagement (CE) is a broad concept encompassing consumers' generic online interactive experiences which can include a brand and/or other consumers (van Doorn et al. 2010).

CE on FBPs includes behavioural (CEB), emotional (CEE) and cognitive (CEC) activities that the consumer undertakes during their interactions with the brand and with other consumers. This thesis investigates CEB (behavioural) and CEE (emotional) but not the cognitive dimension of consumer engagement. Note since this thesis is on FBPs generic CE activities occurring on consumer generated platforms (e.g. review sites, consumer blogs, anti-brand communities) are not considered as these activities entail consumer engagement with other consumers without any involvement of the brand itself. Instead, the focus here is on consumer engagement performed in the context of consumer-to-brand (C2B) and consumer-to-consumer (C2C) interactions on FBPs as a brand generated platform.

Chapter 2 examines the constructs of consumer engagement behaviors enacted in C2B interactions including the liking and sharing of brand content as well as commenting on brand content. The chapter also examines the consumer engagement behaviors enacted in C2C interactions including replying to and liking each other comments. The emotional perspective of consumer engagement is examined in chapter 4 and entails the emotional dynamics in consumer-to-consumer conversations. In particular, the emotional contagion occurring among consumers within C2C conversations is empirically investigated.

Brand Engagement

Brand engagement (BE) includes behavioural (BEB), emotional (BEE) and cognitive (BEC) activities that the brand undertakes during its interactions with consumers. This thesis investigates BEB (behavioural) and BEE (emotional) but not the cognitive dimension of brand engagement. Previous research has mainly focused on consumer engagement and little attention has been devoted to the concept of brand engagement.

This thesis investigates two modalities of brand engagement on FBPs. The first modality, defined as brand initiated engagement, occurs when the brand initiates a consumer conversation by posting a brand related content. The second modality, defined as webcare brand intervention, occurs when the brand replies to consumer comments/requests (reactive brand intervention) and/or opens a discussion thread in consumer conversations by posting a comment to which consumers can reply (proactive brand intervention). Therefore, we consider webcare brand intervention as one form among others of brand engagement in online consumer conversations.

Webcare intervention strategies in online consumer conversations

Brand interventions in online consumer conversations, referred to as webcare interventions (Kerkhof, Beukeboom, and Utz, 2010), are believed to counter the effects of negative consumer engagement (van Noort and Willemsen, 2012) and foster positive consumer engagement (Schamari and Schaefers 2015). Although previous research has provided meaningful insights to further our understanding of webcare interventions in online consumer conversations, much of the academic research investigates webcare as a reaction to either negative or positive consumer engagement, but no study so far has examined the dynamics of webcare interventions in consumer conversations entailing both positive and negative consumer comments. Furthermore, it remains unclear how consumers would react to multiple brands interventions within the same conversation, as previous studies only focus on single interventions. Although previous research provides interesting findings, they rely on observations from experimental settings that fail to capture a more realistic picture of natural settings. Deriving insights from webcare interventions in real consumer conversations reflects real-word situations and increases external validity. Despite significant practitioner interest, little empirical research examines webcare interventions in consumer conversations on Facebook brand pages.

As consumers are no longer passive recipients of information, but rather co-creators and disseminators of brand related content, marketers can take advantage of the unfettered consumer generated content available on social media for marketing decision making (Boyd and Ellison 2007). Furthermore, negative online consumer conversations can go viral and lead to detrimental effects. Indeed, in the current digital context fueling the contagiousness or spillover of negative online chatter, consumers do not only voice their complaints to a broader audience (Berry et al 2010), but they can also actively call for boycotts (Klein et al 2004), or even take part in online revenge and sabotage behaviors (McColl-Kennedy, Sparks and Browning 2010). This can cause potential damage to the brand's reputation which can take a long time to recover from. As such, consumer empowerment is considered as a double-edged sword in the hands of brand marketers.

Consumer brand engagement

In this thesis, the concepts of consumer engagement and brand engagement are considered distinct yet they co-operate in a dynamic and interactive way on FBPs into what we call consumer brand engagement (CBE). To fully capture CBE, we suggest to examine all activities involving both the brand and consumers in the context of brand-to-consumer (C2B), consumer-to-brand (C2B) and consumer-to-consumer (C2C) interactions taking place on FBPs. Therefore, CBE on FBPs is defined as: Consumer engagement with a brand consisting of behavioral (CBEB), emotional (CBEE) and cognitive activities (CBEC) that consumers undertake during their interactions with the brand and with other consumers.

From a behavioral standpoint, this thesis considers CBE behaviors in the context of multiplex interactions occurring on FBPs between the brand and its consumers as well as among consumers through brand-to-consumer (B2C), consumer-to-brand (C2B) and consumer-to-consumer (C2C) interactions. Chapter 2 examines seven CBE behaviors on Facebook brand pages comprising two Brand Engagement Behaviors (BEB) constructs and seven Consumer Engagement Behaviors (CEB) constructs. The chapter also examines how such behavioral constructs interact with each other.

From an emotional standpoint, the thesis addresses how consumers emotionally engage with the brand and with each other. In other words, the co-occurrence of two different emotional contagion mechanisms, one from the brand to consumers (B2C), and the other among consumers (C2C) on FBPs are examined. The emotional aspect of CBE manifests in positive and negative brand related content generated either by consumers and/or brands. Chapter 4 investigates the contagious effect of single and multiple emotions in terms of valence and arousal expressed in brand related content, either generated by the brand (BEE) or by consumers (CEE).

Most of the research to date has predominantly focused on engagement occurring between brands and consumers, with little attention devoted to consumer-to-consumer engagement. This thesis fills this gap by examining the engagement from both the brand perspective and consumer perspective as well as their interplay at the behavioral level (chapters 2 and 3) and emotional level (chapter 4).

Active and passive engagement

Consumer brand engagement is either active or passive. Previous research demonstrates that consumer engagement operates within a dynamic process at different intensity levels capturing different engagement states (Brodie et al, 2013). Other researchers (Dholakia et al, 2009) have emphasized that, when managing online communities, brands play a key role by engaging either actively or passively.

Active brand engagement entails the direct interactions of brands with consumers in online community settings (Homburg, Ehm and Artz, 2015). In the context of FBPs, these direct interactions include the initiation of consumer conversations by posting brand content, replying to consumers' comments or starting a discussion thread by commenting in consumers' conversations. In contrast, passive brand engagement reflects a state of silence or inactivity allowing the brand to stay behind the scenes and simply observe and monitor online consumer conversations without intervening. The brand might choose voluntarily to not engage in conversations among consumers in order to prevent any perception of brand intrusion in "consumer-owned space" (Shamari and Schaefers 2015, p.22).

Active consumer engagement captures the direct interactions of consumers with the brand and with each other to co-create and disseminate brand related content on FBPs. On the one hand, consumers respond to brand posts by writing comments and replying to each other's comments. On the other hand, consumers contribute to pass along the brand-related content (either generated by the brand or by other consumers) by liking it and sharing it with their networks on Facebook. Not all brand community members on FBPs are actively engaged consumers. Indeed, passively engaged consumers, often called "lurkers" (Schlosser, 2005), form the majority of online brand community members (Schneider, Von Krogh, & JäGer, 2013; Walker, Redmond, & Lengyel, 2013). Passively engaged consumers are information recipients who consume brand-related content without contributing back to create and/or disseminate content. Brodie et al. (2013) consider such passive engagement as a temporary state of dormancy which can lead to either re-engagement or permanent disengagement of consumers.

Emotional dynamics on Facebook Brand Pages

In the quest of creating strong relationships with their consumers, brands invest heavily in developing emotional branding strategies. Emotional dynamics refer to the interactive emotional experiences that consumers develop with the brand, as well as with other consumers on Facebook brand pages. Previous research has long recognized the crucial role played by emotions to create strong and sustainable consumer-brand relationships. For instance, Malär et al., (2011) consider that creating an emotional connection between brands and consumers represents "a key branding issue in today's marketing world" (p.35). In the same vein, marketing practitioners (Gobe 2001; Atkin, 2004; Lynch and De Chernatony, 2004; Lindstrom, 2005) have emphasized that establishing an emotionally evocative brand-consumer relationships is highly regarded as a fundamental pillar of brand marketing differentiation which enables brand marketers to achieve a sustainable competitive advantage. In this regard, emotional branding appears to be an effective branding strategy allowing marketers to engage emotionally with consumers.

Emotional branding refers also to a "consumer-centric, relational, and story-driven approach to forging deep and enduring affective bonds between consumers and brands" (Thompson, Rindfleisch, and Arsel 2006, p.50). The tenets of emotional branding suggest that brand marketers should incorporate emotions and inspiring stories in their content to captivate and appeal to consumers' emotions enabling them to forge meaningful affective bonds with their consumers (Atkin, 2004). Although emotional branding has seen a surge in interest among researchers, not much is said about how it affects consumers, particularly in the context of social media. We argue that emotional contagion functions as means to facilitate the execution of emotional branding strategies, through the mimicry in which consumers mimic the brand's and other consumers' emotions during their interactions (e.g. Ekman, Friesen and Scherer 1976). We also argue that a feedback reaction (Lohmann, Pyka and Zanger, 2017) leads consumers to experience the same emotional state as others (Adelmann and Zajonc 1989) and converge emotionally with those who are involved in the relationships (Hatfield, Cacioppo and Rapson, 1994).

Very few research studies investigate emotional contagion on social media, particularly on the Facebook platform. Although some studies provide interesting insights and demonstrate the occurrence of emotional contagion on Facebook among friends, none examined emotional contagion in the context of online branding. This thesis is set out to examine emotional contagion operating between the brand and consumers, as well as among consumers themselves on Facebook brand pages.

Textual and visual aspects of engagement behaviour

In the early days of Twitter, then called twittr, the social media platform built its foundation on the idea of an SMS-like service to communicate short text messages with groups of people. Nowadays, text only content still forms most of branded content on social media platforms with up to 70% of brand tweets being text only (Ross, 2014). Facebook, however, has been driven by visual content from the start with its photo sharing capability. As web technologies and broadband speed evolved over the years, rich audio/visual content has been gradually introduced on social media platforms including the ability to post photos and videos on nearly all of today's social media platforms. Yet, visual content still represents a relatively small proportion of the content shared on social media. For example, less than 10% of brand generated tweets are visual according to Ross (2014). Nevertheless, the top tier of most engaging tweets comprises up to 47% of visual tweets (Ross, 2014), indicating a presumably stronger correlation between visual brand content and consumer engagement. On Facebook too, photos and videos are the most engaging post types (Saric, 2017).

Much of social media content analysis has focused on written (verbal) forms of communication using natural language processing (NLP) and machine learning models for text classification, leaving richer forms of content such as images and videos underutilized in research studies. This is despite the fact that nonverbal communication has been accepted as a formidable source of information (Bull, 2002; Mehrabian, 2009), that online content activating both visual and auditory senses is considered to be more vivid than online text-based content (Coyle and Thorson 2001; Daugherty et al. 2008), and that consumers' emotional reactions to marketing content has been shown to be particularly activated by visual elements of the advertising (Edell 1987).

Analysis of non-verbal communication, such as images, audio and video, is computationally more difficult than text analysis (Swartz and Ungar, 2015). However, with the advent of cloud computing enabling relatively affordable access to large computing resources, visual and speech analysis services are becoming available for marketing practitioners and researchers to embrace. For example, Artificial Intelligence enabled Cognitive Services from Microsoft Azure Cloud services are intelligent algorithms capable of analyzing natural methods of communication including text, audio, images and videos. Emotion API, part of Microsoft's Cognitive Services, reliably detects emotions shown in facial expressions embedded in visual content. Chapter 4 of this thesis is among the very few papers analysing visual social media brand content using AI-enabled emotional analysis of visual data using face detection and evaluating their expressed emotions.

Significance of the research and thesis structure

The momentum gained by social media and the unprecedented empowerment of consumers through their connections to online brand communities have profoundly changed the way consumers engage with brands and with other consumers. These changes challenge brand managers in their quest to take control of online consumer conversations. Given this challenge and lacking research on consumer and brand engagement on Facebook brand pages, the overall objective of this thesis is to further our understanding of the online consumer and brand engagement. The importance of this thesis resides first in its strong empirical foundations driven from large datasets of actual consumer and brand engagement content gathered from several Facebook brand pages across different industry sectors, and the use of advanced big data analysis techniques to unveil practicable insights on consumer brand engagement on Facebook brand pages. This complements existing research in this area that is mainly based on self-reported data or experimental settings.

This thesis sets out to investigate online consumer and brand engagement from different angles through related studies on Facebook brand pages, with three papers written in journal article format. The first paper is an empirical analysis of the interplay between brand engagement and consumer engagement behaviors as well as among consumers themselves on Facebook brand pages. The paper develops a conceptual model of engagement behaviors, translates its components into measurable constructs and empirically investigates the effects of brand engagement on consumer engagement and among consumers in 2,740 Facebook brand pages. The second paper examines the impact of 64,347 webcare interventions embedded within 24,557 consumer conversations on Facebook brand Pages to determine whether type (proactive versus of reactive), voice (personal versus impersonal), timing (early versus late) and number (single versus multiple) of webcare interventions influence the volume and valence of consumer conversations. The third paper tackles the emotional perspective of consumer brand engagement. Drawing on emotional branding and contagion research, the paper examines the dynamics of emotional brand content and consumer reactions in 942 Facebook brand pages.

Along with the three papers there is an introduction and conclusion to the entire thesis and appendices containing related conference papers and another published journal article. The three papers of the thesis are entitled:

1. Brand and Consumer Engagement Behaviors on Facebook Brand Pages: Alternative Measurements and Contributing Factors (target journal: International Journal of Research in Marketing)
2. Webcare Interventions in Consumer-to-Consumer Conversations: An Empirical Investigation on Facebook Brand Pages (target journal: Journal of Interactive Marketing)
3. Emotional Dynamics on Facebook Brand Pages (target journal: Journal of Consumer Research)

Figure 1 summarizes the structure of the thesis.

Chapter 1	**Introduction** Background to the research Significance of the research
Chapter 2	**Paper I - Brand and Consumer Engagement Behaviors on Facebook Brand Pages: Alternative Measurements and Contributing Factors** Empirical analysis of the interplay between brand engagement and consumer engagement behaviors on Facebook brand pages.
Chapter 3	**Paper II - Webcare Interventions in Consumer-to-Consumer Conversations: An Empirical Investigation on Facebook Brand Pages**

	Empirical study of the impact of webcare interventions on consumer conversations on Facebook brand pages
Chapter 4	**Paper III - Emotional Dynamics on Facebook Brand Pages** Empirical study of the emotional perspective of consumer brand engagement on Facebook brand pages.
Chapter 5	**Conclusion** Explanation of the results. Implications of results to marketers, brand managers and academic researchers. Limitations of the research. Future Research.

Figure 1. Framework of the thesis

Conclusion

This chapter introduces the background to the research on consumer brand engagement and highlights opportunities and challenges faced by today's brand marketers, as well as existing research gaps in the study of consumer brand engagement on social media platforms. The chapter provides a concise yet wide overview of the background surrounding the concept of consumer brand engagement on social media. With existing research in the area of consumer brand engagement focused on its scope and dimensions, little research explore the intricacies between brand engagement and consumer engagement behaviors, its emotional dynamics, and the role of webcare strategies to manage consumer conversations on Facebook brand pages. This chapter presents a solid justification for conducting the research. Chapter two presents the first of three papers and examines the interplay between brand and consumer engagement behaviors on Facebook brand pages through a conceptual model of engagement and its associated measurable constructs.

References

Adelmann, P. K., & Zajonc, R. B. (1989), Facial efference and the experience of emotion. *Annual review of psychology*, 40(1), 249-280.

Ashley, Christy, Stephanie M. Noble, Naveen Donthu, and Katherine N. Lemon. (2011), "Why customers won't relate: Obstacles to relationship marketing engagement." *Journal of Business Research*, 64, 7, 749-756.

Atkin, D. (2004), *The culting of brands: When customers become true believers.* Portfolio (Hardcover).

Berry, Leonard L., Ruth N. Bolton, Cheryl H. Bridges, Jeffrey Meyer, A. Parasuraman, and Kathleen Seiders. (2010), "Opportunities for innovation in the delivery of interactive retail services." *Journal of Interactive Marketing*, 24, 2 155-167.

Blau, Peter Michael. (1964), *Exchange and power in social life*. Transaction Publishers.

Bolton, Ruth N. (2011), "Comment: Customer engagement: Opportunities and challenges for organizations." *Journal of Service Research*, 14, 3, 272-274.

Boyd, Danah M., and Nicole B. Ellison. (2007), "Social Network Sites: Definition, History, and Scholarship." *Journal of computer-mediated communication*, 13, 1, 210-230.

Brehm, J. W., & Self, E. A. (1989), The intensity of motivation. *Annual review of psychology*, 40(1), 109-131.

Brodie, Roderick J., Linda D. Hollebeek, Biljana Jurić, and Ana Ilić. (2011), "Customer engagement: Conceptual domain, fundamental propositions, and implications for research." *Journal of Service Research*, 14, 3, 252-271.

Brodie, Roderick J., Ana Ilic, Biljana Juric, and Linda Hollebeek. (2013), "Consumer engagement in a virtual brand community: An exploratory analysis." *Journal of Business Research*, 66, 1, 105-114.

Bull, P. (2002), *Communication under the microscope: The theory and practice of microanalysis*. London, United Kingdom: Psychology Press.

Choudhury, Musfiq Mannan, and Paul Harrigan. (2014), "CRM to social CRM: the integration of new technologies into customer relationship management." *Journal of Strategic Marketing*, 22, 2, 149-176.

Constantinides, E., Romero, C.L., & Boria, M.A.G. (2009), "Social media: A new frontier for retailers?" *European Retail Research*, 22(1), 1–28.

Coyle, James R., and Esther Thorson. (2001), "The effects of progressive levels of interactivity and vividness in web marketing sites." *Journal of advertising*, 30, 3, 65-77.

Daugherty, Terry, Matthew S. Eastin, and Laura Bright. (2008), "Exploring consumer motivations for creating user-generated content." *Journal of Interactive Advertising*, 8, 2, 16-25.

Dessart, L., Veloutsou, C., & Morgan-Thomas, A. (2016), "Capturing consumer engagement: duality, dimensionality and measurement". *Journal of Marketing Management*, 32(5-6), 399-426.

Dholakia, Utpal M., Barbara E. Kahn, Randy Reeves, Aric Rindfleisch, David Stewart, and Earl Taylor. (2010), "Consumer behavior in a multichannel, multimedia retailing environment." *Journal of Interactive Marketing* 24, 2, 86-95.

Drejing, Karl, Serge Thill, and Paul Hemeren. (2015), "Engagement: A traceable motivational concept in human-robot interaction." *In IEEE 2015 International Conference on Affective Computing and Intelligent Interaction (ACII).* 956-961.

Edell, Julie A., and Marian Chapman Burke. (1987), "The power of feelings in understanding advertising effects." *Journal of Consumer research* 14, 3, 421-433.

Ekman, P., Friesen, W. V., & Scherer, K. R. (1976), "Body movement and voice pitch in deceptive interaction." *Semiotica*, 16(1), 23-28.

Facebook (2018), Facebook Reports Fourth Quarter and Full Year 2017 Results, Press Release on Jan. 31, 2018, PRNewswire. Accessed on 15/02/2018 at https://investor.fb.com/investor-news/press-release-details/2018/Facebook-Reports-Fourth-Quarter-and-Full-Year-2017-Results/default.aspx

France, Cassandra, Bill Merrilees, and Dale Miller. (2016), "An integrated model of customer-brand engagement: Drivers and consequences." *Journal of Brand Management*, 23, 2, 119-136.

Gensler, Sonja, Franziska Völckner, Yuping Liu-Thompkins, and Caroline Wiertz. (2013), "Managing brands in the social media environment." *Journal of Interactive Marketing*, 27, 4, 242-256.

Gobe, M. (2001), *Emotional branding*. Paradigma Baru Untuk Menghubungkan Merek Dengan Pelanggan, Penerbit Erlangga, Jakarta.

Hatfield E., Cacioppo, J., & Rapson, R. L. (1994), *Emotional contagion*. New York, Cambridge University Press.

Higgins, E. Tory, and Abigail A. Scholer. (2009), "Engaging the consumer: The science and art of the value creation process." *Journal of Consumer Psychology* 19, 2, 100-114.

Hollebeek, L. D., Glynn, M. S., & Brodie, R. J. (2014), "Consumer brand engagement in social media: Conceptualization, scale development and validation." *Journal of interactive marketing*, 28(2), 149-165.

Hollebeek, Linda D., Rajendra K. Srivastava, and Tom Chen. (2016), "SD logic–informed customer engagement: integrative framework, revised fundamental propositions, and application to CRM." *Journal of the Academy of Marketing Science*. 1-25.

Homburg, Christian, Laura Ehm, and Martin Artz. (2015), "Measuring and Managing Consumer Sentiment in an Online Community Environment." *Journal of Marketing Research*, 52, 5, 629-641.

Jaakkola, Elina, and Matthew Alexander. (2014), "The role of customer engagement behavior in value co-creation: a service system perspective." *Journal of Service Research* 17, 3, 247-261.

Karpen, Ingo O., Liliana L. Bove, and Bryan A. Lukas. (2012), "Linking service-dominant logic and strategic business practice: A conceptual model of a service-dominant orientation." *Journal of Service Research*, 15, 1, 21-38.

Kerkhof, Peter, Camiel Beukeboom, and Sonja Utz. (2010), "The humanization of a company: effects of personal vs. impersonal organizational reactions to negative online consumer reviews." *Etmaal voor de Communicatiewetenschap*, Gent, Belgium.

Klein, Jill Gabrielle, N. Craig Smith, and Andrew John. (2004), "Why we boycott: Consumer motivations for boycott participation." *Journal of Marketing*, 68, 3 92-109.

Lamberton, Cait, and Andrew T. Stephen. (2016), "A thematic exploration of digital, social media, and mobile marketing: research evolution from 2000 to 2015 and an agenda for future inquiry." *Journal of Marketing* 80, 6, 146-172.

Leckie, Civilai, Munyaradzi W. Nyadzayo, and Lester W. Johnson. (2016), "Antecedents of consumer brand engagement and brand loyalty." *Journal of Marketing Management*, 32, 5-6, 558-578.

Lindstrom, M. (2005), "Broad sensory branding." *Journal of Product & Brand Management*, 14(2), 84-87.

Liu, Yuping, and L. J. Shrum. (2002), "What is interactivity and is it always such a good thing? Implications of definition, person, and situation for the influence of interactivity on advertising effectiveness." *Journal of advertising* 31, 4, 53-64.

Lohmann, Katja, Sebastian Stefan Pyka, and Cornelia Zanger. (2017), "The effects of smileys on receivers' emotions." *Journal of Consumer Marketing* 34, 6, 489-495.

Lusch, Robert F., and Stephen L. Vargo. (2006), "Service-dominant logic: reactions, reflections and refinements." *Marketing theory* 6, 3, 281-288.

Lynch, Joanne, and Leslie De Chernatony. (2004), "The power of emotion: Brand communication in business-to-business markets." *Journal of Brand management* 11, 5, 403-419.

Malär, Lucia, Harley Krohmer, Wayne D. Hoyer, and Bettina Nyffenegger. (2011), "Emotional brand attachment and brand personality: The relative importance of the actual and the ideal self." *Journal of marketing* 75, 4, 35-52.

McColl-Kennedy, Janet R., Beverley A. Sparks, and Doan T. Nguyen. (2011), "Customer's angry voice: Targeting employees or the organization?" *Journal of Business Research*, 64, 7 707-713.

Mehrabian, A. (2009), *Nonverbal communication* (3rd ed.). Piscataway, NJ: Aldine Transaction.

Meng, Qingguo, Nan Zhang, Xuejiao Zhao, Fangling Li, and Xin Guan. (2016), "The governance strategies for public emergencies on social media and their effects: a case study based on the microblog data." *Electronic Markets*, 26, 1, 15-29.

Pham, M.T. and Avnet, T. (2009), "Rethinking Regulatory Engagement Theory", *Journal of Consumer Psychology*, 19 (2), 115-123.

Precourt, Geoffrey. (2016), "How is consumer engagement reshaping marketing?" *Journal of Advertising Research*, 56, 1, 2-3.

Richter, Daniel, Kai Riemer, and Jan vom Brocke. (2011), "Internet social networking." *Business & Information Systems Engineering*, 3, 2, 89-101.

Saric, Marko. (2017), "The State of Facebook Video In The Year 2017: Video Length Up, Time Watched Down", Business2Community blog, https://www.business2community.com/facebook/state-facebook-video-year-2017-video-length-time-watched-01834666

Ross, Phillip (2014), "Photos get the Most Engagement on Twitter", SocialBakers blog, https://www.socialbakers.com/blog/2306-photos-get-the-most-engagement-on-twitter

Sasser, Sheila, Mark Kilgour, and Linda D. Hollebeek. (2014), "Marketing in an Interactive World: The Evolving Nature of Communication." *Harnessing the Power of Social Media and Web Analytics* 29.

Schamari, Julia, and Tobias Schaefers. (2015), "Leaving the home turf: how brands can use webcare on consumer-generated platforms to increase positive consumer engagement." *Journal of Interactive Marketing*, 30 20-33.

Schivinski, Bruno, George Christodoulides, and Dariusz Dabrowski. (2016), "Measuring Consumers' Engagement With Brand-Related Social-Media Content." *Journal of Advertising Research*, 56, 1, 64-80.

Schlosser, Ann E. (2005), "Posting versus lurking: Communicating in a multiple audience context." *Journal of Consumer Research* 32, 2, 260-265.

Schneider, Andreas, Georg Von Krogh, and Peter JäGer. (2013), "“What’s coming next?” Epistemic curiosity and lurking behavior in online communities." *Computers in Human Behavior* 29, 1, 293-303.

Schwartz, H. Andrew, and Lyle H. Ungar. (2015), "Data-driven content analysis of social media: a systematic overview of automated methods." *The ANNALS of the American Academy of Political and Social Science* 659, 1, 78-94.

Sensis (2015), *Social Media Report May 2015 - How Australian people and businesses are using social media*.

Skinner, Ellen A., Thomas A. Kindermann, James P. Connell, and James G. Wellborn. (2009), "Engagement and disaffection as organizational constructs in the dynamics of motivational development." *Handbook of motivation at school*, 223-245.

Thompson, Craig J., Aric Rindfleisch, and Zeynep Arsel. (2006), "Emotional branding and the strategic value of the doppelgänger brand image." *Journal of marketing* 70, 1, 50-64.

van Doorn, Jenny, Katherine N. Lemon, Vikas Mittal, Stephan Nass, Doreén Pick, Peter Pirner, and Peter C. Verhoef. (2010), "Customer engagement behavior: Theoretical foundations and research directions." *Journal of service research*, 13, 3, 253-266.

van Noort, Guda, and Lotte M. Willemsen. (2012), "Online damage control: The effects of proactive versus reactive webcare interventions in consumer-generated and brand-generated platforms." *Journal of Interactive Marketing*, 26, 3 131-140.

Vargo, Stephen L., and Robert F. Lusch. (2004), "Evolving to a new dominant logic for marketing." *Journal of marketing*, 68, 1, 1-17.

Vargo, Stephen L., and Robert F. Lusch. (2008), "Service-dominant logic: continuing the evolution." *Journal of the Academy of marketing Science*, 36, 1, 1-10.

Vivek, Shiri D., Sharon E. Beatty, and Robert M. Morgan. (2012), "Customer engagement: Exploring customer relationships beyond purchase." *Journal of Marketing Theory and Practice*, 20, 2, 122- 146.

Walker, Beth, Janice Redmond, and Andras Lengyel. (2010), "Are they all the same? Lurkers and posters on the net." *eCULTURE* 3, 1, 16.

Chapter 2: Introduction to paper I

The first paper in the thesis, entitled "Brand and Consumer Engagement Behaviors on Facebook Brand Pages: Alternative Measurements and Contributing Factors" is an empirical analysis of the interplay between brand engagement behaviors (BEBs) and consumer engagement behaviors (CEBs) on Facebook brand pages as well as among consumers themselves. The paper starts by providing a brief overview of the literature related to Consumer Brand Engagement and discusses the limitations in the way industry and academia measure engagement on Facebook. A conceptual model identifying both BEBs and CEBs on Facebook brand pages is then proposed and their practicable components are translated into measurable constructs. BEBs are decomposed into brand presence and brand responsiveness, while CEBs are decomposed into endorsement, feedback, recommendation, conversation and consensus. The conceptual model also explores how BEB components independently influence CEB components and how several factors play a moderating role in increasing consumer engagement behaviors including the format and timing of brand content posted on Facebook. The conceptual model further distinguishes how the different CEB components interact, reflecting how consumers influence each other. To empirically test the model, a large scale analysis of 525,000 brand posts, 1,706,656 consumer comments and 64,729 brand replies published on 2,740 Facebook brand pages was conducted.

"Brand and Consumer Engagement Behaviors on Facebook Brand Pages: Alternative Measurements and Contributing Factors" is targeted for submission to the International Journal of Research in Marketnig. The paper is presented in this thesis in the journal's required publication format yet for ease of reading tables and figures are embedded throughout. The contribution ratio for this paper is outlined in the Acknowledgements section of the thesis.

Brand and Consumer Engagement Behaviors on Facebook Brand Pages: Alternative Measurements and Contributing Factors

Chedia Dhaoui [a*], Cynthia M. Webster [b]

Macquarie University, Sydney, Australia

[a] chedia.dhaoui@mq.edu.au , [b] cynthia.webster@mq.edu.au

Abstract

As social media continues to gain momentum in the new digital marketing landscape, consumers are increasingly empowered in their engagement with brands and with one another, challenging firms to measure and manage the performance of consumer brand engagement. This paper proposes a conceptual model capturing the interplay between brand engagement behaviors and consumer engagement behaviors as well as among consumers themselves. The model is empirically evaluated using more than 525,000 brand posts, 1,706,656 consumer comments and 64,729 brand replies published on 2,740 Facebook brand pages across 25 industries over a twelve month period. Results demonstrate a significant effect of brand presence and responsiveness on consumer engagement behaviors as well as a significant effect of consumer engagement behaviors on each other, and several interaction effects between consumer engagement behaviors. Further analyses indicate significant moderating effects of format of brand posts and promptness of brand replies to consumer comments. Findings also demonstrate a 'negativity effect' within consumer interactions. Negative feedback has a stronger negative effect on consumer conversations than positive feedback and highly recommended posts with high negative feedback are associated with both increased positive and negative conversations. Taken together, these findings shed light on how marketers can design and implement more effective social media marketing strategies.

Keywords: Social media marketing; Consumer brand engagement; Facebook brand pages.

Introduction

Among the Web 2.0 technologies that have emerged in the last decade, social media has sparked a profound change in the way brands engage with consumers. Social networking sites, such as Facebook, are potent interactive marketing tools. As of the last quarter of 2016 over 60 million businesses have Facebook brand pages, up from 18 million in 2013, 30 million in 2014 and 40 million in 2015. This remarkable growth of over 20 million new business pages in the last year alone, along with up to 32% of Facebook users following their favorite brands on Facebook (Sensis 2015), indicate the importance of Facebook for today's businesses motivated by the substantial benefits that can be gained from using social media platforms.

Facebook's appeal as the social media platform of choice for brands to engage with consumers is not just a matter of audience size but also thanks to its multi-directional and multi-modal communication capabilities. On Facebook, interactions are not restricted to a one-to-one dialogue between brands and consumers, instead they extend to consumer networks (Meng et al. 2016) and occur among consumers themselves (Choudhury and Harrigan 2014). Facebook brand pages provide online community members the opportunity to connect, produce and share online content, which allow brands to take advantage of unfettered consumer generated content (Boyd and Ellison 2007). Brands also enrich consumption experiences by reaching out to consumers on a personal level, monitoring their activities, replying to their comments and even influencing their conversations (Mangold and Faulds 2009). These interactive experiences between consumers, the brand and other members of the brand community are what marketers call consumer brand engagement (CBE) (Hollebeek, Glynn and Brodie 2014).

Practitioners and researchers continue to investigate the scope and dimensions of CBE (Brodie et al. 2013; Cvijikj and Michahelles 2013; Mollen and Wilson 2010) with less attention given to decipher the intricacies between brand engagement behaviors (BEBs) and consumer engagement behaviors (CEBs) within online communities. Peters et al. (2013) point out that effective measurement is a prerequisite for managing social media. However, prior studies rarely collect actual observed behaviors from social media sources, but instead use self-reports of online activity which can stray far from actual usage patterns on social networking websites.

Although CBE is frequently measured by marketing research firms, its measurement is often taken with a grain of salt, as the variety of calculation methods often leads to different results and inconsistencies among studies (Macnamara 2014). Recent work identifies the need for: 1) more specific concepts of engagement, 2) the use of large datasets of recorded behaviors to develop observed measures of engagement and 3) evidence regarding the effectiveness of social media marketing activities for stimulating consumer engagement (Calder, Malthouse and Maslowska 2016; Maslowska, Malthouse and Collinger 2016).

This paper addresses these points and aims to: 1) provide a conceptual model identifying both BEBs and CEBs on Facebook brand pages, 2) translate practicable components of online engagement behaviors into measurable constructs and 3) empirically investigate the effects of BEBs on CEBs as well as CEBs on each other. This research makes several important contributions which form the structure for this article. We first give a brief overview of CBE related literature and discuss limitations in industry and academic measurement practices. To provide specificity, we then identify the components of BEBs and CEBs and explain their measurement on Facebook brand pages. We propose a conceptual model showing how BEB components independently influence CEB components with moderators of brand post format, timing and promptness of brand replies to consumer comments. The conceptual model further distinguishes how the different CEB components influence each other. We then test the model using data from 2,740 Facebook brand pages consisting of more than 525,000 brand posts, 1.7 million consumer comments and 64,000 brand replies posted over a twelve month period spanning 25 industries.

Literature review

Conceptualization of consumer brand engagement

Conceptually, CBE sits within the broader context of engagement, shaped by the theoretical perspectives of social exchange theory (Blau 1964), service-dominant logic (Vargo and Lusch

2004, 2008; Karpen et al. 2012) and relationship marketing theory (Vivek et al. 2012; Ashley et al. 2011). Although receiving considerable interest and emerging as a highly influential concept in contemporary marketing (Precourt 2016), CBE is still at an early stage of understanding (France et al. 2016). The growing body of engagement research in marketing provides a multiplicity of engagement-based concepts. See Brodie et al. (2011) and Dessart, Veloutsou and Morgan-Thomas (2016) for a comprehensive overview of engagement conceptualizations and Leckie, Nyadzayo and Johnson (2016) for a summary of key CBE definitions. Although engagement concepts vary, most agree with Brodie et al. (2011, p. 259) that "specific interactive experiences are an indispensable component of a customer's particular engaged state" and that these interactions take place between a specific "engagement subject" (e.g. consumer) and "engagement object" (e.g. brand, product, or website).

Much of the consumer engagement research is conceptual in nature with efforts devoted to scale development distinguishing one or many of the cognitive, emotional and behavioral dimensions of CBE (Hollebeek et al. 2014; Dessart, Veloutsou and Morgan-Thomas 2016). Some scholars emphasize the cognitive and affective components of engagement considering engagement as a psychological state (Brodie et al., 2011), psychological process (Bowden 2009), emotional connection (Chan and Li 2010), intrinsic enjoyment (Calder, Malthouse and Schaedel 2009), state of mind (Hollebeek 2011a), passion (Hollebeek 2011b), or enthusiasm (Vivek et al. 2012). This perspective stands in contrast with a practitioner-oriented view that focuses on the behavioral manifestations of engagement (e.g. Schivinski, Christodoulides and Dabrowski 2016; Jaakkola and Alexander 2014) which go beyond purchase transactions, including word-of-mouth activities, referrals, recommendations and blogging (MSI 2010). While the psychological view of CBE has provided important contributions, we argue greater attention needs to be placed on understanding and measuring CBE behaviors, especially given the direct linkage with brand strategy and their importance for managerial action (Bolton 2011).

Existing approaches measuring CBE behaviors on Facebook brand pages

Brand managers recognize the pressing need to engage with consumers and the strategic importance of CBE, but as Hollebeek et al. (2014, p.150) point out “insights into consumers' engagement-related dynamics remain sparse and largely lacking measurement capability and empirical validation to date”. Although there has been several attempts to measure CBE whether in industry or in academic research, two key debates remain unsettled.

The first issue about CBE measurement pertains to whether CBE should be measured as a single, composite metric, summing several behaviors or multiple metrics distinguishing different engagement behaviors. Most of the existing CBE measurement models use a single metric of CBE. Collapsing different engagement behaviors performed on Facebook brand pages into a single number allows brand managers to easily track, report and compare CBE over time and across brands. However, marketing and advertising scholars argue that using a single metric to assess CBE is problematic as it is unlikely to fully capture marketing communication efforts and related performance outcomes (e.g. Ambler and Roberts 2008; Schultz et al. 2004; Taylor 2010). According to Peters et al. (2013) distinct metrics are needed to capture the dynamics that reflect the immediate and multi-way nature of social media interactions (i.e. how certain metrics are more influential than others and how they are inter-correlated).

The second issue pertains to which engagement behaviors are included in the measurement of CBE. For instance, marketing academics and practitioners alike often partially cover all BEBs and CEBs in their measurement of CBE because they have predominantly focused on the interactivity between brands and consumers, while consumer-to-consumer interactivity remains unexplored along with the influence of consumers’ engagement on each other. Furthermore, certain engagement behaviors, such as the act of commenting on Facebook brand pages, is often wrongly considered as a single type of engagement behavior and no distinction is made between commenting on brand posts and replying to other consumer comments. Discrepancies also exist among CBE measurement approaches as most industry practitioners do not differentiate between active engagement (i.e. likes, comments and shares) and passive engagement (i.e. clicks to view content) which can lead to an overestimation of engagement. For instance, Fulgoni (2016) finds click-through rate is not a relevant metric to measure engagement due to the lack of relationship with advertisement effectiveness.

Current CBE measurement models implemented in industry practices adopt three approaches, as summarized in Table 1, all of which suffer from the limitations described above. The first measurement approach, adopted by Facebook, captures the number of consumers who engage with the brand. Facebook considers consumers as engaged when they click, like, share or comment on brand posts. While this method measures the size of the engaged audience, it does not reflect the intensity of engagement, as consumers might engage multiple times with brand posts, yet are only counted once. The second approach, adopted by Hootsuite, Quintly as well as Facebook, calculates the engagement per post as the total number of interactions on a brand page including reactions (i.e., like, love, haha, wow, sad and angry), comments and shares rather than counting the number of engaged consumers. Unlike the first method, this approach reports the intensity of engagement. TrueSocialMetrics adopts a similar approach but measures each form of engagement behavior separately rather than combining them into a single metric.

The third approach, adopted by Social Backers, consists of calculating an engagement rate relative to the size of the brand community (i.e., number of fans) which is arguably used to compare engagement across brand posts or across brands having different community sizes. Daily page engagement rate is the average number of likes, shares and comments per post on a given day divided by the total number of brand fans on that same day. The rationale behind it is that an engagement rate of 50% would mean that half the community of brand fans have engaged with the brand post on a given day. The engagement rate relative to the number of brand fans on Facebook brand pages is based on the assumption that brand posts are viewed by the entire brand community on Facebook, which is far from reality when it comes to how Facebook manages audiences among brand community members. Indeed, Facebook displays brand posts on the news feed of selected fans based on the match between the brand post content and the profiles of brand fans as well as their historical behaviors. Furthermore, the number of fans constantly changes, such that a ratio metric relative to the number of fans cannot be used to capture social media engagement behaviors over time. In contrast to Social Bakers, Facebook calculates the engagement rate as the number of engaged consumers divided by the number of consumers being reached by brand posts, the reach corresponding to all consumers who had the post in their news feed.

Table 1. An overview of selected industry practices on CBE measurement

Approach	Company	CBE concept & measurement model
Measuring the number of **consumers** who have engaged with brand posts	Facebook	Engagement = total number of consumers who engaged with brand posts (reactions, comments, shares or clicks on brand posts)
Measuring the number of **interactions** between consumers and brand posts	Facebook	Post Engagement = the total number of interactions per post (reactions, comments, shares and clicks)
	Hootsuite	Overall engagement = the total number of interactions on a page (reactions, comments, and shares)
	TrueSocialMetrics	Conversation rate = the total number of comments per post Amplification rate = the total number of shares per post Applause rate = the total number of likes per post
	Quintly	Average interactions (likes, shares, comments) per Post
Measuring consumer interactions with brand posts **as a ratio**	Facebook	Engagement Rate = $\frac{total\ number\ of\ consumers\ who\ engaged\ with\ brand\ posts}{total\ number\ of\ consumers\ brand\ posts\ have\ reached}$
	Socialbakers	Daily page engagement rate = $\frac{\frac{\#Likes\ +\#Comments+\ \#Shares\ on\ a\ given\ day}{\#\ of\ brand\ posts\ on\ a\ given\ day}}{Total\ \#fans\ on\ a\ given\ day} \times 100$

Existing academic efforts to measure CBE behaviors on social media, summarized in Table 2, are affected by shortcomings pertaining to their validity, comprehensiveness, availability of their underlying social media metrics and data sources considered. Many academic studies rely primarily on self-reported data (e.g. Schivinski, Christodoulides and Dabrowski 2016; Dessart, Veloutsou and Morgan-Thomas 2016; Hollebeek et al. 2014), which can differ from observed behavior due to responder and recall biases (Donaldson and Grant-Vallone 2002). The few studies that do rely on actual behavioral data from social media platforms tend to rely on opaque industry metrics such as Engagementdb's Engagement Score and Klout score (Ashley and Tuten 2015) or replicate the limitations of existing industry measurement practices described above (Oviedo-García et al. 2014; Cvijikj and Michahelles 2013). Furthermore, they do not take into account all BEBs and CEBs such as brand interventions in consumer-to-consumer interactions, consumer replies to comments and the sharing of brand posts (De Vries et al. 2012).

Table 2. Relevant research on CBE behaviors' measurement on social media

CBE measurement based on self-reported data
Gummerus J. and Liljander V. (2012) *Description:* Empirical study using data gathered via an online survey of Facebook brand community members of an online gaming provider. *CBE Concept:* Customer engagement Behaviors in a brand community on Facebook *Measurement model:* Community Engagement Behaviors (CEB) and Transactional Engagement Behaviors (TEB) measured in terms of frequency of brand community visits, content liking, commenting, news reading, frequency of playing, and money spent on the internet gaming site. *Key findings*: Investigated the consequences of customer engagement behaviors and not their antecedents.
Jahn B. and Kunz W. (2012) *Description:* Empirical study using data gathered via a survey of 523 brand fan-page members *CBE Concept:* Fan page engagement. *Measurement model:* Fan-page engagement measured in terms of customers' community participation, identification, and integration. *Key findings:* Functional and hedonic content attracts users to fan pages. Interaction among fan-page members and with the brand itself enhance fan-page engagement. The fan page's ability to enhance social self-concept is also associated with higher fan-page engagement.
Kabadayi S. and Price K. (2014) *Description:* Empirical study using data gathered via an online national survey from 269 respondents. *CBE Concept:* Consumers' liking and commenting behavior on Facebook brand pages. *Measurement model:* Facebook behavior in terms of Liking and Commenting. *Key findings:* Consumers' broadcasting mode of interaction was positively related to both liking and commenting behaviors. The communicating mode of interaction had a positive relationship with liking behavior and a negative relationship with commenting behavior.
Hollebeek L. D. et al. (2014) *Description:* Scale development using data gathered via a survey of 194 undergraduate business students *CBE Concept:* Consumer brand engagement *Measurement model:* The measurement of brand engagement on social media in based on cognitive processing, affection, and activation. *Key findings:* Consumer brand 'involvement' was found to exhibit a significant relationship with each of the three CBE factors of cognitive processing, affection and activation.
De Vries N. J. and Carlson J. (2014) *Description:* Empirical study using data gathered via a survey of 404 students in Australia.

CBE Concept: Customer engagement with Facebook brand pages.

Measurement model: Drawn from Jahn and Kunz (2012), customer engagement is measured in terms of community participation, identification, and integration.

Key findings: Co-creation value, social value, usage intensity and brand strength influence consumer engagement with brand pages.

Dessart et al. (2016)

Description: Scale development using data gathered via an online survey of 448 fans of Facebook brand pages in various industry sectors.

CBE Concept: Brand engagement and Community engagement

Measurement model: Brand engagement and Community engagement as two foci, each broken down into Enthusiasm, Enjoyment, Attention, Absorption, Sharing, Learning, and Endorsing.

Schivinski et al. (2016)

Description: Scale development using three qualitative studies (online focus groups, online depth interviews and netnography) followed by two quantitative studies to validate and test the measurement instrument.

CBE Concept: Consumers' engagement with brand related social media content

Measurement model: Consumption (e.g. see a picture or watch a movie displaying), Contribution (e.g. comment, like or share brand related content), and Creation of brand related social media content.

CBE measurement based on industry data

De Vries L. et al. (2012)

Description: Empirical study using data gathered manually from 11 Facebook brand pages across 6 product categories and 355 brand posts.

CBE Concept: Popularity of Brand Posts on Brand Fan Pages

Measurement model: Brand post popularity in terms of #Likes and #Comments on brand posts.

Key findings: Highly vivid or interactive brand posts enhance the number of likes. The position of a brand post at the top of the brand fan page has a positive effect on the number of likes and comments. Shares of positive and negative comments enhance the number of comments.

Cvijikj & Michahelles (2013)

Description: Empirical study using data gathered from 100 Facebook brand pages of FMCG in the food and beverages industry.

CBE Concept: Engagement

Measurement model: Likes Ratio (#Likes / #Fans); Comments Ratio (#Comments / #Fans); Shares Ratio (#Shares / #Fans); Interaction Duration (Time of last interaction / Time of post creation).

Key findings: Content type (Entertainment, Information, and Remuneration), media type (Vividness, Interactivity) and posting time (weekdays, off-peak hours) have been found to have an effect on engagement.

Oviedo-García et al. (2014)

Description: Conceptual paper proposing a metric for customer engagement on Facebook.

CBE Concept: Customer engagement on Facebook

Measurement model: Ratio of interest = (#Likes+#Comments+#Shares+#Other clicks) / #Posts; Ratio of effective interest = Ratio of interest / Average impressions; Engagement on Facebook = Ratio of effective interest / Average reach.

Ashley C. and Tuten T. (2015)

Description: Empirical study using data gathered manually corresponding to social media content associated with 28 brands.

CBE Concept: Social Media Engagement

Measurement model: Social popularity (#Fans on Facebook and #Followers on Twitter); Social influence (Klout score from www.klout.com); Engagement Score (from Engagementdb).

Key findings: Brands that use the most social media channels have more followers and higher engagement scores. The use of user-image appeals and exclusivity appeals has significant correlations with the number of Facebook fans. Resonance, animation, experiential appeals, and connections with social causes have significant correlations with a brand's Klout score. Incentives for participation lead to more consumers following the brand on Twitter as well as a higher Klout scores and Engagement Scores.

Yang S. et al. (2016)

Description: Empirical study using multitrait-multimethod (MTMM) approach comprising industry data provided by Socialbakers about a single brand on Facebook and survey data from 108 university undergraduate students for reliability and validity tests.

CBE Concept: Brand engagement

Measurement model: Affiliation (daily measure of the increase in the number of fans for the Facebook brand page); Conversation (daily number of individual Facebook users who are talking about the brand on their own wall); and Responsiveness (total number of likes, comments and shares of the brand content posted on the Facebook brand page)

Although the number of behavioral engagement options for brands and consumers has grown dramatically since the advent of web 2.0 technologies and social media applications (Van Doorn et al. 2010), much of academic research and industry practice predominantly focuses on CEBs and the active role of consumers in brand-related interactions (Wallace, Builand de Chernatony 2014) with little attention given to the dynamic relationships reflecting brand-to-consumer and consumer-to-consumer interactivities (Maslowska, Malthouse and Collinger 2016). As no existing study to date measures CBE behaviors comprehensively, the approach adopted in this paper to measure CBE has several advantages over existing ones. First, we consider CBE behaviors in the context of multiplex interactions occurring on Facebook brand pages between the brand and its consumers as well as among consumers through brand-to-consumer (B2C), consumer-to-brand (C2B) and consumer-to-consumer (C2C) interactions. Second, we propose a set of metrics capturing CBE behaviors in terms of modality (i.e., the forms of behavior), valence (i.e., either positive or negative) and volume (i.e., number of occurrences of behavior). By considering this larger set of metrics, the proposed measurement approach enables detailed insights on the mechanisms underlying the inter-relationships among CBE behaviors on Facebook brand pages.

Conceptual model and research hypotheses

The conceptual model in Figure 1 proposes seven CBE behaviors on Facebook brand pages comprising two BEB constructs and seven CEB constructs. On the one hand, BEB constructs consist of brand presence behavior, capturing how the brand posts content on its Facebook brand page, and brand responsiveness behavior, referring to how the brand responds to consumer comments. On the other hand, CEB constructs comprise endorsement behavior, which reflects the behavior of liking brand posts, recommendation behavior capturing the behavior of sharing brand posts, feedback behavior (both positive and negative) through commenting on brand posts, conversation behavior (both positive and negative) through replying to consumer comments, and consensus behavior capturing the behavior of liking consumer comments. We also distinguish positive and negative valence of both feedback and conversation behaviors. The conceptual model indicates direct effects of BEB constructs on CEB constructs and moderating effects of brand post format (i.e. text, link, photo, video), timing of brand posting (i.e. day/night, weekday/weekend), and promptness of brand replies to consumer comments.

The model examines also the interactions amongst CEBs (effect of feedback behaviors on conversation behaviors and the effect of both feedback and conversation behaviors on consensus behavior). The industry sector and the seasonal effects are considered as well.

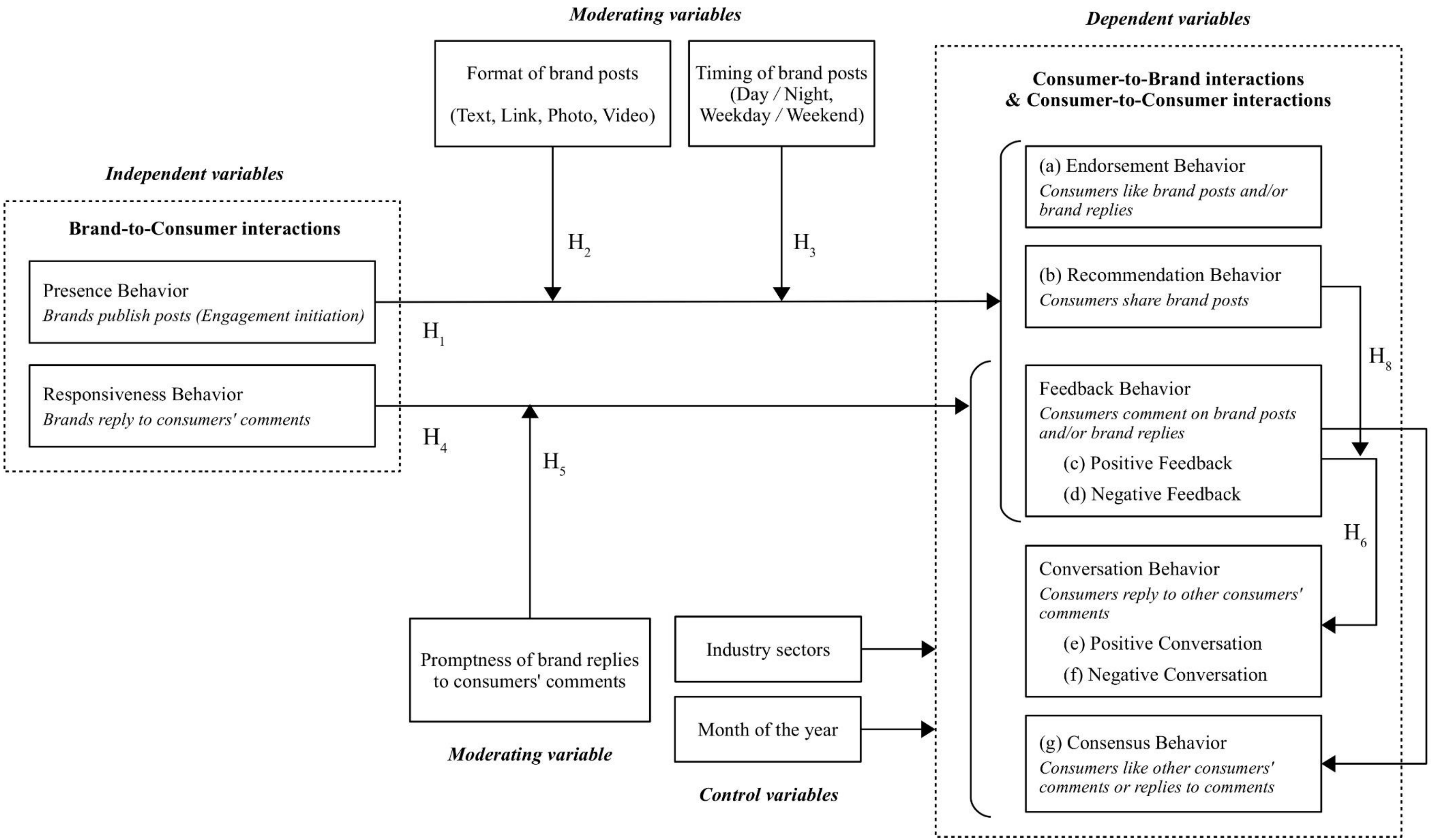


Figure 1. Conceptual model of CBE behaviors on Facebook brand pages

Consumer Engagement Behaviors (CEBs): Endorsement, Feedback, Recommendation, Conversation and Consensus

Considering engagement on Facebook brand pages from a consumer standpoint, CEBs capture all consumer behaviors performed in the context of C2B and C2C interactions. Exposed to brand posts as a brand initiated stimuli, most consumers are passive recipients of brand-related information (Sawhney et al. 2005) by "lurking" or taking a "consumptive form of community participation" (Hartmann, Wiertz, and Arnould 2015, p. 319; Mousavi, Roper and Keeling 2017). However, engaged consumers actively interact with the brand post (C2B interactions) or with one another (C2C interactions). They can endorse the brand post by liking it, provide feedback by commenting positively or negatively, recommend the brand post to friends by sharing it, engage in conversations with other consumers by replying to other consumers' comments, or express consensus through liking other consumers' comments. This level of interactivity with the brand and with one another is enabled by the networked nature of social media which affects the relationships between consumers and brands beyond the consumer-brand dyad to incorporate the broader social network context in which consumers and brands are embedded (Kozinets et al., 2010). Consumers are empowered by social media technologies, enabling them to gain a more important voice, share their brand stories widely with peers (Gensler et al. 2013) and potentially influence other consumers (Lamberton and Stephen 2016).

Endorsement Behavior

Liking content on Facebook brand pages is the most common engagement behavior on Facebook with over 4 million likes happening every minute. When consumers "like" brand generated content, such as a brand post or a brand comment, they actually demonstrate their endorsement of such content. A high level of endorsement behavior means that the brand content appeals to the consumers and catches their attention. The act of liking brand content illustrates the support from brand community members, their appreciation and/or their agreement with the content published by the brand.

Feedback Behavior

Social media provides a novel community-driven platform allowing consumers to provide direct comments about new product concepts, features and consumer experiences (Peppler and Solomou 2011; Barker 2008). The volume of comments created by the brand's community is a good indicator of how well members are engaging via a feedback loop (Evans 2010; Garber Jr., Hyatt and Boya 2009). On Facebook, comments are "threaded" which means that there are two types of comments: top level comments and replies to top level comments. When consumers create top level comments on a brand post, they provide feedback to the brand through C2B interactions. They also provide feedback when replying to a brand generated comment.

Feedback behavior can be positive or negative, which are important to distinguish. Studies find negative consumer comments to have detrimental effects on brand evaluation, purchase behavior and brand loyalty (Chevalier and Mayzlin 2006; Chiou and Cheng 2003) whereas positive consumer engagement improves attitude and leads to favorable behavior (Brodie et al. 2013; Seraj 2012). Therefore, feedback behavior is delineated into positive and negative constructs. Positive feedback refers to the behaviors of posting positive top level comments on brand posts or positive replies to brand comments while negative feedback refers to the behaviors of posting negative top level comments on brand posts or negative replies to brand comments.

Recommendation Behavior

The act of sharing brand posts on Facebook is at the core of what makes social media content go viral (Berger and Milkman 2012). When consumers click the share button of a brand post, they pass along brand content to their friends in their social network. This behavior is widely adopted as Allsop, Bassett and Hoskins (2007) found that 59% of people frequently pass along online content to others. Previous research shows that recommendation and persuasion are key motives for sharing content on social networks (Berger 2014). A high level of recommendation behavior reflects the viral characteristics of brand posts and their psychological effects on a user's motivation to share it with peers (Berger and Heath 2005; Heath, Bell and Sternberg

2001). Several researchers suggest that consumers recommend online brand related content for goal-oriented motivation and self-serving purposes, to signal their identity, develop social relationships and influence others (Chung and Darke 2006; Wolny and Mueller 2013). Highly recommended brand content typically includes entertaining, useful, or unique information that serves self-image and social bonding purposes (Berger 2014).

Conversation Behavior

When consumers generate feedback, other consumers have the opportunity to respond, which then creates conversational threads through C2C interactions among consumers themselves within the brand community. While positive and negative feedback reflect the reaction of consumers to brand content, conversations are driven by the brand community members around particular debatable topics expressed by the brand community itself, although triggered by the post published by the brand in the first place. Similar to feedback behaviors, conversation behaviors are delineated into positive and negative constructs. Positive conversations refer to consumers posting positive replies to consumer comments while negative conversation refers to consumers posting negative replies to consumer comments. Existing research on C2C interactions in online brand communities highlights its positive effect on purchase intentions and sales (Adjei, Noble and Noble 2010), but no prior work has examined the conversational interactions among consumers on Facebook brand pages.

Consensus Behavior

Along with commenting and replying to comments, consumers can also “like” comments to express their agreement with the content posted by other consumers. This behavior reflects the level of consensus consumers reach in their conversations and represent an additional indicator of consumer engagement. The behavior of liking consumer comments forms an indicator of consensus across the brand community on Facebook. The question is whether consensus tends to form around negative or positive comments. Existing work is limited to investigate the behavior of liking brand posts, but no prior research has examined the behavior of consumers liking each other’s comments.

Brand Engagement Behaviors (BEBs): Presence and Responsiveness

Considering engagement behaviors initiated by the brand on Facebook brand pages, two types of brand behaviors are possible: posting brand content or replying to consumer comments. Brand posts are typically brand generated content containing text, photos, videos or links that represent brand initiated “stimuli” appearing on consumers' Facebook news feeds. As brands post content more frequently, their presence on consumers' Facebook news feeds increases too, along with the exposure they gain among their Facebook community members. Research shows that when consumers see the brand as interactive, they feel welcomed, encouraged to engage and valued by the brand which helps to form trust and strengthen the consumer brand relationship (Merrilees and Fry 2003). Therefore, we expect that (H1) higher brand presence leads to increased C2B engagement behaviors towards the brand posts, namely their endorsement by consumers, their recommendation to peers and the consumer feedback they generate.

Not all brand posts stimulate the same level of engagement as both the format (i.e., text, links to websites, photos, videos) and scheduling (i.e., time of day and day of the week) matter. The various media formats used convey different levels of richness, interactivity and vividness. Sensory rich media that appeal to multiple senses depict situations in ways that approximate reality and increase immersion (Shrum 2002). For instance, online content activating both visual and auditory senses is considered to be more vivid than online text-based content (Coyle and Thorson 2001; Daugherty et al. 2008). Although results are mixed on whether vividness has a positive or negative effect on consumer attitudes toward Facebook brand posts (Chauhan and Pillai 2013; De Vries et al. 2012; Sabate et al. 2014), previous research shows that consumers are more likely to engage and spread messages that contain arousing content (Berger and Milkman 2012; Dellarocas, Gao & Narayan 2010). As such, we expect (H2) media format to moderate the relationship between brand presence and CEBs towards brand posts, increasing endorsement, feedback and recommendation behaviors when brand posts contain photos or videos.

In addition to media format, the scheduling of marketing communications is an important factor leading to increased interaction and revenue (Kumar et al. 2006). Being present and accessible means posting during the times in which the brand's community members are more likely to engage with the published content. Research emphasizes that consumers spend more time on Facebook during weekends looking for fun and social interaction (Schulze et al. 2014). As such, we expect (H3) media scheduling (or the timing of the brand posts) to moderate the relationship between brand presence and CEBs towards brand posts, increasing endorsement, feedback and recommendation behaviors when brands post during weekends compared to week days, and when brands post during off-peak hours compared to peak hours.

As brand presence triggers CEBs including consumers commenting on brand posts, brand managers can passively monitor consumer conversations and choose not to intervene, or play a more active role by responding to consumer comments. Brand responsiveness fosters further CEBs by leveraging positive consumer comments (Hennig-Thurau et al. 2010; Vivek, Beatty and Morgan 2012) or moderating negative consumer conversations (Fournier and Avery 2011). Such effects are of particular managerial interest given the influence of negative online word-of-mouth (WOM) has on other consumers, even when they have a positive brand experience (Schlosser 2005). Despite significant practitioner interest, not many empirical studies investigate brand responsiveness to consumer engagement on Facebook brand pages and social media in general. Most notably, Miller and Tucker (2013) show that active management of a community stimulates user generated content. Other work looks at different types of brand intervention strategies, such as proactive versus reactive (van Noort and Willemsen 2011) and personal versus impersonal (Schamari and Schaefers 2015). One study examines the intensity and quickness of firm engagement in online forums (Homburg, Ehm and Artz 2015) and finds that consumers respond with diminishing returns to active firm engagement. Other studies have examined brand responsiveness to negative WOM for online damage control (van Noort and

Willemsen 2011) with results showing that negative WOM can be attenuated when brands are responsive. When consumers comment on brand posts, they expend effort above and beyond the usual exchange relationship to provide information to benefit the brand. Evidence indicates that organizations can increase the strength of their relationships with consumers if they effectively recognize the value they place on consumers' exchange efforts (Vincent and Webster 2013). Considering brand responsiveness as an indicator of the frequency of brand replies to consumer comments, we expect that (H4) brand responsiveness has a stronger positive relationship with Positive Feedback and Positive Conversation than Negative Feedback and Negative Conversation, and has a positive relationship with Consensus behavior.

We also consider the promptness of brand replies to consumer comments, based on the average time lapse between a consumer comment and when the brand replies. As pointed out by van Noort and Willemsen (2012), when brands respond to consumers' negative word-of-mouth in a timely manner, they demonstrate that they care about their consumers' issues (Hong and Lee 2005; van Laer and de Ruyter 2010). Thus, we expect that (H5) the promptness of brand replies to consumer comments moderates the effect of brand responsiveness on conversation and consensus behaviors.

Consumer-to-Consumer (C2C) Interactions amongst Consumer Engagement Behaviors (CEBs)

Few studies empirically examine CEBs in the context of C2C interactions on Facebook brand pages. Relling et al.'s (2016) work investigates the effect of CEBs on the active participation of brand communities on Facebook (number of comments and likes), but does not provide insights on the valence of consumer comments as reactions to other consumers' negative or positive comments. Ferrara and Yang's (2015) study on Twitter demonstrates a linear relationship between the valence of the content that users are exposed to and that of the responses they generate. Indeed, positive word-of-mouth leads to positive brand evaluations (East, Hammond and Loamax 2008) and negative word-of-mouth leads to negative brand evaluations (Chiou and Cheng 2003; Chen and Lurie 2013). Moreover, studies indicate a "negativity effect" (Ahluwalia 2002) with negative information often considered as more memorable, diagnostic, salient, deeply processed, and more likely to be shared than positive information (Ito et al. 1998; Pratto & John 1991).

These results together with work by Ein-Gar et al. (2012) suggest that positive consumer feedback on Facebook brand pages leads to positive consumer conversations and agreement among consumers which has a beneficial effect and negative consumer feedback leads to negative consumer conversations and agreement which has a detrimental effect. Research, however, also shows that in some instances negative online word-of-mouth can have positive effects (Berger et al. 2010). Consumers who feel a close personal connection to the brand cognitively combat negative information (Sherman and Cohen 2006) and are more likely to engage in defending the brand against negative online word-of-mouth (Wilson, Biebelhausen and Brady 2017). In these situations negative consumer feedback in the form of comments and replies can generate positive conversations. The 'negativity effect' logically extends to consumer recommendation behavior with consumers compelled to defend the brand for highly shared posts that attract high negative consumer feedback.

Given that online social networking platforms such as Facebook foster contagiousness through consumer-to-consumer interactivity (Lamberton and Stephen 2016), and those consumers who invest effort in engaging with the brand and one another tend to have stronger connections to the brand, we hypothesize that (H6) consumer feedback (positive and negative) has a positive relationship with consumer conversation (both positive and negative). We also expect that (H6a) positive consumer feedback has a stronger relationship with positive conversation and negative feedback has a stronger relationship with than negative conversation, and (H6b) the effect of negative feedback on negative conversation is stronger than the effect of positive feedback on positive conversation. Moreover, we expect that (H7) consumer feedback and consumer conversation behaviors (positive and negative) to be positively related to consensus behavior with feedback having a stronger relationship compared to conversation.

We also hypothesize an interaction effect such that (H8) high negative feedback for highly recommended brand posts (but not for low recommended posts) increases both positive and negative consumer conversation.

Research method

Description of the data collection and pre-processing

To examine CBE behaviors on Facebook brand pages, this study gathered company data recorded on the 2015 Inc.5000, an annual list published by Inc. Magazine comprising the 5000 fastest-growing private companies in the U.S. across 32 industry sectors. Company data provided by the 2015 Inc.5000 and relevant for this study included the corresponding industry sector and the official website. Every year, the Inc.5000 list ranks companies according to their revenue growth over the previous four-year period. A manual verification process involved visiting each of the 5000 listed companies' websites to identify its corresponding Facebook brand page. Companies without an official Facebook brand page and those no longer independently operating were excluded from the sample as access to their original Facebook brand pages was not possible. In addition, companies having more than one Facebook brand page were also excluded as the presence of multiple Facebook brand communities may diffuse or dilute consumer engagement and thus are not comparable to brands with a single Facebook community. We refined the sample of Facebook brand pages considered in this study by selecting those whose community size exceeded 100 fans and who published at least one brand post during 2015.

As a result, a total of 2740 out of the initial 5000 companies (54.8%) across 25 industry sectors passed the eligibility criteria and their Facebook brand pages were considered for the remainder of the study. To simplify the data analysis and interpretation of results, the 25 industry sectors were categorized into five segments adapted from the UN high-level aggregation of the International Standard Industrial Classification (ISIC) of all economic activities (ISIC revision 4 2008). Table 3 shows the distribution across the five industry categories considered in this study.

Table 3. Sample distribution across industry sectors

Industry category	Sample size	%
Ind1. Business products and services *Business Products & Services (257), Human Resources (124), Advertising & Marketing (313)*	694	25.3%
Ind2. Information and Communication Technologies *Computer Hardware (16), IT Services (366), Software (218), Telecommunications (62)*	662	24.2%
Ind3. Consumer products and services *Consumer Products & Services (139), Food & Beverage (88), Retail (101), Travel & Hospitality (39), Financial Services (110), Insurance (39), Real estate activities (87)*	603	22.0%
Ind4. Manufacturing, construction and industrial activities *Construction(105), Energy (41), Engineering (32), Manufacturing (86), Logistics & Transportation (81), Security (49)*	394	14.4%
Ind5. Public services *Education (44), Environmental Services (21), Government Services (81), Health (210), Media (31)*	387	14.1%

Facebook's social graph Application Programming Interface (API) was used to collect all publicly data available on the 2740 Facebook brand pages considered in this study. Twelve months' worth of interaction data were collected covering the period from 1st January 2015 to 31st December 2015. Due to the large amount of data requested from Graph API, cloud computing resources on Amazon Web Services (AWS) were provisioned to ensure efficiency of data collection and analysis. The scalability of cloud infrastructure allows one to reach any required IT performance during data collection and transformation. In the current study, cloud resources were used to improve the reliability and speed of Graph API queries thanks to the high level of network bandwidth available in the cloud (Internet speed).

The collected data included all brand posts along with all associated CEBs corresponding to likes, shares, comments and replies to comments as well as brand replies to consumer comments. To assess the valence of brand posts, we used LIWC2015 (Pennebaker et al. 2015), a text analysis software that measures the degree of use for various categories of words in text-based documents. LIWC supports a sentiment lexicon (dictionary) for positive and negative emotions and has been widely used in psychology and linguistics (Tausczik and Pennebaker 2010). The dictionaries of LIWC2015 accommodate short phrases and "netspeak" language that is common in Twitter and Facebook posts and SMS-like modes of communication (Pennebaker et al. 2015). For example, "b4" is coded as a preposition and ":)" is coded as a positive emotion word (Pennebaker et al. 2015). The software calculates the relative frequency of positive and negative words in a given text sample (e.g., the words “love”, “nice”, or “sweet” are counted as positive valence, while the words “hurt”, “ugly”, “nasty” are counted as negative valence). Overall, 620 positive words and 744 negative words are used in LIWC2015.

Coding and measurements

Coding of the brand generated posts consisted of identifying the type of media used in brand posts, the time of brand posts release and the valence of the brand content itself. Media type included text only, photo, link and video. The time of releasing a brand post was categorized as peak (7am to 7:59pm) and off-peak (8pm to 6:59am) times, for both the work week (Monday-Friday) and weekends (Saturday-Sunday). Because we wanted to assess the relationship between BEBs with CEBs as well as the relationship among CEBs themselves, we had to generate variables that measure each of the brand engagement constructs and consumer engagement constructs. Table 4 displays the variables used in this study to assess the hypothesized relationships. Absolute consumer engagement on the post level captures the number of CEBs (i.e. likes on brand post, shares of brand post, comments on brand post, consumer replies to other consumer comments and likes on consumer comments) of the respective post. We also included fixed effects of the respective quarter of the year to control for seasonality effects such as summer/winter sales periods, or the Christmas season (time fixed effects). Given that this study uses data over a 12 months period (1st January 2015 to 31st December 2015), CEB constructs and BEB constructs are aggregated monthly into 12 measurements for each brand, one for every month of the year.

Table 4. Summary of variables used in this study

Variables	**Measures**
Measurement of independent variables (Brand Engagement Constructs)	
Brand Presence (BP)	The number of posts published by the brand on its Facebook brand page. This variable is operationalized as a monthly measure, counting the number of posts published by the brand for each month.
Brand Responsiveness (BR)	The number of brand replies posted by the brand on its Facebook brand page. Brands can either pick and respond to a particular consumer comment or reply to the conversation in general. This variable is operationalized as a monthly measure of responsiveness, counting the number of brand replies for each month.
Measurement of dependent variables (Consumer Engagement Constructs)	
Endorsement (END)	The number of likes on brand posts. This variable is operationalized as a monthly measure of endorsement, capturing the sum of the endorsement of brand posts for each month.
Recommendation (REC)	The number of shares of brand posts. Similarly to the endorsement measure, this variable is also operationalized as a monthly measure of recommendation, capturing the sum of the recommendation of brand posts for each month.
Positive Feedback (PF)	The amount of positive (respectively negative) consumer comments on brand posts. Consumer comments are classified as either positive or negative using a lexicon based sentiment classifier (LIWC2015). Similarly to the endorsement and recommendation measures, these variables are also operationalized as monthly measures capturing the sum of the positive (respectively negative) feedback on brand posts for each month.
Negative Feedback (NF)	
Positive Conversation (PC)	The amount of positive (respectively negative) consumer replies to other consumer comments on brand posts. These variables are operationalized as monthly measures capturing the sum of the positive (respectively negative) conversation on brand posts for each month.
Negative Conversation (NC)	
Consensus (CONS)	The number of likes of consumer comments. This variable is also operationalized as a monthly sum of consensus.
Measurement of moderating variables	
Promptness of brand replies (PROMPT)	The number of hours (rounded up) lapsed between a consumer comment and its brand reply in the conversation. When brand replies are not responding to a particular comment, its promptness is measured as the lapse between the first consumer comment on the brand post and the brand reply. The variable is operationalized as a monthly measure of promptness, averaging the promptness of brand replies for each month. The variable is also inverted (1/x) so that it is higher for prompt replies, and it is equal 0 when no brand replies are found for a given month.

Type of brand posts Photo (PH) Video (VID) Other (Link, Text) (OTH)	Three dummy variables that indicates with 1 if a brand post is respectively in the form of a photo, a video, or other form of content (either link or text) and 0 otherwise. The variable is also operationalized as a monthly measurement corresponding to the proportions of photo, video or other posts for each month.
Timing of brand posts Off Peak Hours (OPEAK) Weekend (WEND)	Dummy variable OPEAK that assumes the value of 1 if a brand post is published during peak off-peak hours (8pm to 6:59am), and 0 otherwise. Dummy variable WEND that assumes the value of 1 if a brand post is published during the weekend (Saturday or Sunday), and 0 otherwise. Both dummy variables are operationalized as monthly measurements corresponding to the proportion of posts published during off-peak hours and weekends respectively.
Measurement of control variables	
Brand specific variables: industry sector Five dummy variables, one for each industry category, that assume the value of 1 if the brand belongs the respective industry category, and 0 otherwise. Industry categories include: Business products & services (IndBiz), Information & Communication Technologies (IndICT), Consumer products & services (IndCons), Manufacturing & industrial activities (IndMan), and Public services (IndPub).	
Seasonal effect Four dummy variables, one for each quarter of the year, that assume the value of 1 if the observation relates to the respective quarter, and 0 otherwise.	

Empirical model specification

Given our conceptual model proposes multiple relationships of several independent variables with several moderated dependent variables observed over time and aggregated monthly for multiple brands, a multivariate multilevel regression analysis is conducted. At level 1 Endorsement, Recommendation, Positive and Negative Feedback, Positive and Negative Conversation and Consensus are considered as multiple outcomes which at level 2 are nested within brands, and at level 3 are nested within their industry sector. Adopting a multivariate multilevel analytical framework provides two distinct advantages. On the one hand, it provides comparable assessments of the BEB predictors brand presence and brand responsiveness that affect each of the CEBs. On the other hand, it permits an assessment of whether CEBs differ by industry sector, after accounting for the brand level relations between the BEB predictors and CEBs. In contrast to a more traditional approach with data aggregation and repeatedmeasures ANOVA analysis, multilevel multivariate regression contains both fixed and random effects. Fixed effects are directly estimated through the joint estimation of a system of equations (Zellner 1962) while random effects are taken into account and reflect the variances from one brand context to another (Chib and Greenberg 1995) including the variances across brands within the same industry sector and the variances across industry sectors. We additionally control for the seasonal effect by partitioning the full year of observations into four quarters.

Equations 1 to 7 in Table 5 show the system of regression equations corresponding to the seven dependent variables considered in this study. To be consistent with the assumptions of regression analysis, variables that were heavily skewed have been log-transformed. This helps to approximate a normal distribution. Equations 1 and 2 reflect the log-transformed endorsement and recommendation constructs and their dependence on the brand presence, moderated by the format of brand posts (photo and video; other format being used as a baseline) and the timing of brand posts (off-peak and weekend; peak and weekday are being used as baselines). Equations 3 and 4 display the log-transformed positive and negative feedback constructs and their dependence on the brand presence moderated by the format of brand posts and the timing of brand posts, as well as their dependence on brand responsiveness moderated by the promptness of brand replies. Equations 5 and 6 reflect the log-transformed positive and negative conversation constructs and their dependence on the brand responsiveness, moderated by the promptness of brand replies, and the positive and negative feedback constructs to account for the effect of the valence and volume of consumer feedback on other consumers' replies, moderated by the level of recommendation achieved by the brand posts. Finally, equation 7 displays the log-transformed consensus construct and its dependence on the brand responsiveness, moderated by the promptness of brand replies, the positive and negative feedback and conversation constructs, moderated by the level of recommendation achieved by the brand posts.

Table 5. System of equations for multivariate multilevel regression analysis

(1)	$Log(END) = \beta_0 + \beta_1\ Log(BP) + \beta_2\ PH \times Log(BP) + \beta_3\ VID \times Log(BP) + \beta_4\ OPEAK \times Log(BP) + \beta_5\ WEND \times Log(BP) + \beta_6\ Q2 + \beta_7\ Q3 + \beta_8\ Q4$
(2)	$Log(REC) = \beta_0 + \beta_1\ Log(BP) + \beta_2\ PH \times Log(BP) + \beta_3\ VID \times Log(BP) + \beta_4\ OPEAK \times Log(BP) + \beta_5\ WEND \times Log(BP) + \beta_6\ Q2 + \beta_7\ Q3 + \beta_8\ Q4$
(3)	$Log(PF) = \beta_0 + \beta_1\ Log(BP) + \beta_2\ PH \times Log(BP) + \beta_3\ VID \times Log(BP) + \beta_4\ OPEAK \times Log(BP) + \beta_5\ WEND \times Log(BP) + \beta_6\ Log(BR) + \beta_7\ PROMPT \times Log(BR) + \beta_8\ Q2 + \beta_9\ Q3 + \beta_{10}\ Q4$
(4)	$Log(NF) = \beta_0 + \beta_1\ Log(BP) + \beta_2\ PH \times Log(BP) + \beta_3\ VID \times Log(BP) + \beta_4\ OPEAK \times Log(BP) + \beta_5\ WEND \times Log(BP) + \beta_6\ Log(BR) + \beta_7\ PROMPT \times Log(BR) + \beta_8\ Q2 + \beta_9\ Q3 + \beta_{10}\ Q4$
(5)	$Log(PC) = \beta_0 + \beta_1\ Log(BR) + \beta_2\ PROMPT \times Log(BR) + \beta_3\ Log(PF) + \beta_4\ Log(NF) + \beta_5\ Log(PC) + \beta_6\ Log(NC) + \beta_7\ Log(REC) \times Log(PF) + \beta_8\ Log(REC) \times Log(PF) + \beta_9\ Q2 + \beta_{10}\ Q3 + \beta_{11}\ Q4$
(6)	$Log(NC) = \beta_0 + \beta_1\ Log(BR) + \beta_2\ PROMPT \times Log(BR) + \beta_3\ Log(PF) + \beta_4\ Log(NF) + \beta_5\ Log(PC) + \beta_6\ Log(NC) + \beta_7\ Log(REC) \times Log(PF) + \beta_8\ Log(REC) \times Log(PF) + \beta_9\ Q2 + \beta_{10}\ Q3 + \beta_{11}\ Q4$
(7)	$Log(CONS) = \beta_0 + \beta_1\ Log(BR) + \beta_2\ PROMPT \times Log(BR) + \beta_3\ Log(PF) + \beta_4\ Log(NF) + \beta_5\ Log(PC) + \beta_6\ Log(NC) + \beta_7\ Q2 + \beta_8\ Q3 + \beta_9\ Q4$

Results

As presented in Table 6, the dataset for this study includes 525,075 posts, 1,706,656 consumer comments and 64,729 brand replies to consumer comments. Descriptive analyses of the data show brand posts consist of 224,184 photos (42.7%), 250,252 links (47.7%), 27,677 text only status updates (5.3%), and 22,962 videos (4.4%). Most brands post during peak-hours (93.4%) and on weekdays (88.9%). Endorsement behavior is the most widely adopted CEB on Facebook brand pages with the majority of brand posts receiving likes (72.7%) resulting in over 59.9 likes per post on average. Recommendation behavior is the next most common with 38.4% of brand posts being shared at least once, and the number of shares per post averaging 13.9. Fewer consumers provide feedback by commenting on brand posts with only 15.9% of posts receiving feedback for an average of 1.26 feedback per brand post. Positive feedback occurs more often than negative feedback (1.10 vs. 0.16 feedback per post). Consumer conversations follow the same trend with 4.1% of posts generating consumer conversations, averaging 0.21 consumer replies to comments per brand post. Brand responsiveness to consumer feedback is relatively low with only 4.7% of comments receiving brand responses. Finally, consumer consensus is occurring in 13.8% of brand posts, generating 2.17 likes of comment per post.

Table 6. Descriptive statistics of raw data

Brand Presence (#Posts)	N	Proportion	**Brand Responsiveness**	N	Proportion
All	525,075	1.00	All	64,729	1.00
Photos	224,184	0.42	Top level brand comments	8,939	0.14
Video	22,962	0.04	Brand replies to consumer comments	55,790	0.86
Link	250,252	0.47	Mean per post	0.12	
Text (status update)	27,677	0.05	Max per post	686	
Posted during weekdays	466,666	0.89	Proportion of posts having brand responses	4.7% of posts	
Posted during peak hours	490,461	0.93	Number of consumer comments receiving brand replies: 18,770 (1%)		

Consumer Engagement	Endors. (#Likes)	Recomm. (#Shares)	Feedback			Conversation			Consensus (#Likes of comments)
			Positive	Negative	Either	Positive	Negative	Either	
N	31,474,137	7,306,048	580,069	83,905	663974	88,777	19,938	108,715	1,138,949
Mean per post	59.9	13.9	1.10	0.16	1.26	0.17	0.04	0.21	2.17
SD per post	670.1	1147.3	17.51	4.20	19.45	5.64	1.66	7.21	55.66
Max per post	248,022	579,575	4144	1769	4,211	3,268	803	4,071	22,921
% of posts	72.7%	38.4%	15.1%	4.4%	15.9%	3.8%	1.3%	4.1%	13.8%

Monthly aggregated data is shown in Table 7. Brand presence (which captures posting frequency per month) averages 18.8 brand posts per month (median of 11.0). Certain industries have stronger brand presence than others with consumer products and services scoring the highest brand presence (26.2 posts per month) and manufacturing, construction and industrial having the lowest (13.2 posts per month). Brands take 24.6 hours on average to reply to consumers' comments (median of 9.8). The most responsive brands belong to the information and communication technologies industry sector (IND 2), replying to consumers' comments in 16.8 hours on average (median of 4.8). When comparing industry categories, consumer products and services are ahead of the other industry categories in all CEBs except the recommendation behavior which is highest in public services.

Table 7. Descriptive statistics of monthly aggregate engagement data

Monthly Aggregate Engagement			Level 1: multivariate outcomes (n=27,928) *consumer level statistics*		
			Mean	SD	Max
Endorsement (monthly number of likes of brand posts)			1,127.00	13,265.64	980,486
Recommendation (monthly number of shares of brand posts)			261.60	5,784.05	622,642
Positive Feedback (monthly number of positive consumer comments)			21.19	203.77	12,840
Negative Feedback (monthly number of negative consumer comments)			32.41	344.62	20,779
Positive Conversation (monthly number of positive replies to consumer comments)			3.32	37.09	3,297
Negative Conversation (monthly number of negative replies to consumer comments)			4.01	49.22	4,428
Consensus (monthly number of likes of consumer comments)			38.77	413.62	24,107
			Level 2: brands (n=2,740) *Brand level statistics*		
Brand Presence in posts per month			18.80	32.49	1,240
Brand Responsiveness in replies per month			0.89	3.32	91
Brand Response Time in hours of delay			24.61	64.48	1,841
Photo format (monthly proportion of posts)			0.43	0.34	1.00
Video format (monthly proportion of posts)			0.04	0.10	1.00
Other format (monthly proportion of posts)			0.51	0.35	1.00
Day timing (monthly proportion of posts)			0.90	0.19	1.00
Night timing (monthly proportion of posts)			0.10	0.19	1.00
Weekday timing (monthly proportion of posts)			0.93	0.13	1.00
Weekend timing (monthly proportion of posts)			0.07	0.13	1.00
	Level 3: industry sectors (n=5) Industry level statistics (*mean monthly engagement per industry sector)*				
	IndBiz	*IndICT*	*IndCons*	*IndMan*	*IndPub*
Brand Presence in posts per month	15.76	17.19	<u>26.32</u>	13.23	19.90
Brand Responsiveness in replies per month	0.34	0.31	<u>2.16</u>	0.60	1.04
Brand Response Time in hours of delay	20.34	16.86	25.40	24.94	<u>31.61</u>
Endorsement in likes of brand posts per month	131.58	335.55	<u>3454.90</u>	340.97	1155.11
Recommendation in shares of brand posts per month	20.94	37.85	537.78	63.67	<u>824.18</u>
Positive Feedback in comments per month	2.75	4.42	<u>67.05</u>	4.80	22.51
Negative Feedback in comments per month	2.79	5.92	<u>101.70</u>	10.19	37.22
Positive Conversation in replies to comments per month	0.27	1.26	<u>8.88</u>	0.57	5.83
Negative Conversation in replies to comments per month	0.26	1.78	<u>10.63</u>	0.77	6.74
Consensus in likes of comments per month	5.07	15.89	<u>100.81</u>	11.80	62.02

<u>Underlined</u>: maximum

Hypothesis tests

To examine the relationships among consumer and brand engagement behaviors as well as their moderating factors, we conduct a multivariate multilevel regression using the lme4 package in R (Bates et al. 2013). Variance inflation factors (VIF) for the set of predictors (independent, moderating and control variables) for each predicted outcome range from a low of 1.21 to a high of 5.09 indicating an acceptable level of multicollinearity (Hair et al. 1998; Menard 1995). Dropping outliers beyond 99% levels for all variables shows that the results remain unchanged for direction of effects and statistical significance.

Table 8 provides the results of the multivariate multilevel regression analysis explaining a combination of direct and interaction effects on C2B and C2C engagement behaviors. Brand presence is positively related to endorsement, feedback and recommendation. The strongest relationships are with endorsement ($\beta=0.49$, $p<0.001$) and recommendation ($\beta=0.42$, $p<0.001$), and to a lesser extent with positive feedback ($\beta=0.22$, $p<0.001$) and negative feedback ($\beta=0.19$, $p<0.001$). Moreover, these associations vary across brands, given their significant random slopes, but their positive associations remain significant (95% prediction interval: 0.18 to 0.50). Together these results provide support to hypothesis H1 with brand presence positively related to C2B engagement behaviors.

Results for media format show a positive direct relationship between visual posts (either photos or videos) and endorsement, recommendation and feedback, compared to non-visual posts (either text or links). Photos have a stronger relationship with endorsement behavior ($\beta=0.14$, $p<0.001$) than videos ($\beta=0.04$, $p<0.001$), while videos have a slightly stronger relationship with recommendation behavior ($\beta=0.05$, $p<0.001$) than photos are ($\beta=0.04$, $p<0.001$). This indicates that photos are liked more often than videos and videos tend to be shared slightly more often than photos. Photos also have a stronger relationship with the feedback behavior ($\beta=0.10$, $p<0.001$ for positive feedback and $\beta=0.08$, $p<0.001$ for negative feedback) compared to videos ($\beta=0.04$, $p<0.001$ for both positive and negative feedback).

Table 8. Multilevel Multivariate Regression results

		Outcome variables: Consumer Engagement Behaviors (log transformed)													
		END		REC		PF		NF		PC		NC		CONS	
Fixed effects		B	S.E	B	S.E	B	S.E	B	S.E	B	S.E	B	S.E	B	S.E
	Intercept	-0.02	0.08	-0.08	0.07	-0.06	0.04	-0.06	0.04	-0.32***	0.01	-0.31***	0.01	0.01*	0.01
H1	Brand Presence (BP)	0.49***	0.01	0.42***	0.01	0.22***	0.01	0.19***	0.01						
H2	Photo format	0.14***	0.00	0.04***	0.00	0.10***	0.00	0.08***	0.00						
	Video format	0.04***	0.00	0.05***	0.00	0.04***	0.00	0.04***	0.00						
	Photo format × BP	0.05***	0.00	0.04***	0.00	0.05***	0.00	0.04***	0.00						
	Video format × BP	0.02***	0.00	0.03***	0.00	0.02***	0.00	0.02***	0.00						
H3	Night timing	0	0.00	0.01	0.00	0.00	0.00	0.00	0.00						
	Weekend timing	-0.01***	0.00	-0.01**	0.00	0.00	0.00	0.00	0.00						
	Night timing × BP	0	0.00	0	0.00	0.00	0.00	0.00	0.00						
	Weekend timing × BP	-0.01**	0.00	0	0.00	0.00	0.00	0.00	0.00						
H4	Brand Responsiveness (BR)					0.27***	0.01	0.26***	0.01	0.11***	0.01	0.08***	0.01	0.04***	0.01
H5	Promptness					0.01	0.01	0.00	0.01	-0.02**	0.01	-0.01.	0.01	0.02***	0.01
	Promptness × BR					0.01.	0.00	0.01.	0.00	0.02***	0.00	0.01**	0.00	-0.01**	0.00
H6	Positive Feedback (PF)									0.12***	0.01	0.06***	0.01	0.48***	0.01
	Negative Feedback (NF)									0.16***	0.01	0.18***	0.01	0.35***	0.01
H7	Positive Conversation (PC)													0.08***	0.01
	Negative Conversation (NC)													0.06***	0.01
H8	Recommendation									-0.04***	0.01	-0.03***	0.01		
	Recommendation × PF									0.06***	0.01	-0.01	0.01		
	Recommendation × NF									0.21***	0.01	0.29***	0.01		

Time: Quarter 1 (baseline)	–		–		–		–		–		–		–	
Time: Quarter 2	-0.01*	0.01	-0.01	0.01	-0.03***	0.01	-0.04***	0.01	0.03**	0.01	0.03**	0.01	0.00	0.01
Time: Quarter 3	-0.01.	0.01	0.05***	0.01	-0.02**	0.01	-0.02***	0.01	0.12***	0.01	0.11***	0.01	-0.01	0.01
Time: Quarter 4	-0.02**	0.01	0.03***	0.01	-0.01	0.01	-0.03***	0.01	0.13***	0.01	0.12***	0.01	-0.01	0.01
Random effects	σ2	S.D	σ2	S.D	σ2	S.D	σ2	S.D	σ2	S.D	σ2	S.D	σ2	S.D
Between-brands variance														
Intercept	0.40	0.63	0.38	0.61	0.20	0.44	0.19	0.44	0.03	0.17	0.04	0.19	0.04	0.20
Slope Brand Presence	0.04***	0.20	0.05***	0.22	0.05***	0.23	0.05***	0.21						
Slope Brand Responsiveness					0.21***	0.08	0.04***	0.21	0.02***	0.15	0.02***	0.15	0.01***	0.07
Between-industry-sector variance	0.03***	0.17	0.02***	0.14	0.00***	0.06	0.00***	0.06	0.00	0.01	0.00	0.02	0.00***	0.03
Between-industry-sector deviance	Deviance		Deviance		Deviance		Deviance		Deviance		Deviance		Deviance	
Business Products & Services	-0.10		-0.13		-0.05		-0.06		0.00		0.00		0.02	
Information & Communication Technologies	-0.16		-0.11		-0.07		-0.05		0.01		0.01		-0.01	
Consumer products & services	0.28		0.22		0.15		0.14		0.01		0.02		-0.03	
Manufacturing, const. & industrial activities	-0.03		-0.03		-0.02		-0.01		-0.01		-0.02		0.00	
Public services	0.01		0.04		-0.01		-0.01		0.00		0.00		0.02	
#Brands: 2,740 — #Observations	27,928		27,928		27,928		27,928		15,806		15,806		15,808	
#Industry categories: 5 — Conditional R^2	0.87		0.81		0.74		0.74		0.86		0.86		0.91	

β = standardized parameter estimate; S.E: Standard Error; σ^2 = Variance component; S.D: Standard Deviation;

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

The interaction effects of visual media formats (photo and video) and brand presence are also significant and positive with photos increasing the effect of brand presence on endorsement ($\beta=0.05$, $p<0.001$), recommendation ($\beta=0.04$, $p<0.001$), positive feedback ($\beta=0.05$, $p<0.001$) and negative feedback ($\beta=0.04$, $p<0.001$) when compared to links and text formats. Likewise, videos moderate the relationship between brand presence and endorsement ($\beta=0.02$, $p<0.001$), recommendation ($\beta=0.03$, $p<0.001$), positive feedback ($\beta=0.02$, $p<0.001$) and negative feedback ($\beta=0.02$, $p<0.001$) but have a weaker moderating effect than photos. Together these findings provide support for H2, indicating that the positive effect of higher brand presence on C2B behaviors on Facebook brand pages is strengthened when visual media formats are used in brand posts, with photos overall producing even better results than videos.

The effect of brand post scheduling (H3) is not supported as only a few relationships are significant and in the opposite direction as hypothesized. Results show a negative direct relationship between weekend posting and both endorsement ($\beta=-0.01$, $p<0.001$) and recommendation ($\beta=-0.01$, $p<0.01$), and no significant relationship with feedback behavior. There is a negative moderating effect on the relationship between brand presence and endorsement ($\beta=-0.01$, $p<0.01$), and the timing of brand posts in terms of peak/off-peak hours is not significant and do not provide a clear indication on the optimal “time” for posting.

In support of H4, brand responsiveness is positively associated with C2B and C2C engagement behaviors, including positive feedback ($\beta=0.27$, $p<0.001$), negative feedback ($\beta=0.26$, $p<0.001$), positive conversation ($\beta=0.11$, $p<0.001$), negative conversation ($\beta=0.08$, $p<0.001$), and consensus ($\beta=0.04$, $p<0.001$). Moreover, these associations vary across brands, given their significant random slopes, but their positive associations remain significant (95% prediction interval: 0.01 to 0.28). Note that brand responsiveness is almost equally strongly associated with positive feedback as with negative feedback and to a lesser extent to conversation and consensus behaviors. While the association between brand responsiveness and positive conversation is stronger than the association with negative conversation, and therefore contributes to energize positive conversation which is consistent with prior research

(Schamari and Schaefers 2015), the association between brand responsiveness and negative conversation is also significant and therefore further stimulates negative conversations. This finding contrasts with previous research on the role of webcare interventions as means to attenuate negative online brand evaluations (van Noort and Willemsen 2012).

Turning to H5 on brand reply promptness, results show a significant, negative direct effect of brand reply promptness on positive conversation (β=-0.02, $p<0.01$) and a significant, positive effect on consensus behavior (β=0.02, $p<0.001$). This suggests that, when brands respond too quickly to consumer feedback, they tend to impede subsequent positive consumer conversation but foster consensus with no significant impact on negative conversation. The significant, positive interaction effects between promptness and brand responsiveness on positive conversation (β=0.02, $p<0.001$) and negative conversation (β=0.01, $p<0.001$) show that when brand replies are both frequent and prompt, consumer conversations are positively affected, benefitting positive conversation more than negative conversation. The significant, negative interaction effect for consensus behavior indicates that promptness only matters for brands that infrequently respond. These interaction effects are visually depicted in Figure 2. Following Aiken and West (1991), the interactions are plotted at the minimum (maximum) value of a variable if one standard deviation below (above) the mean is smaller (larger) than the minimum (maximum) value of the variable.

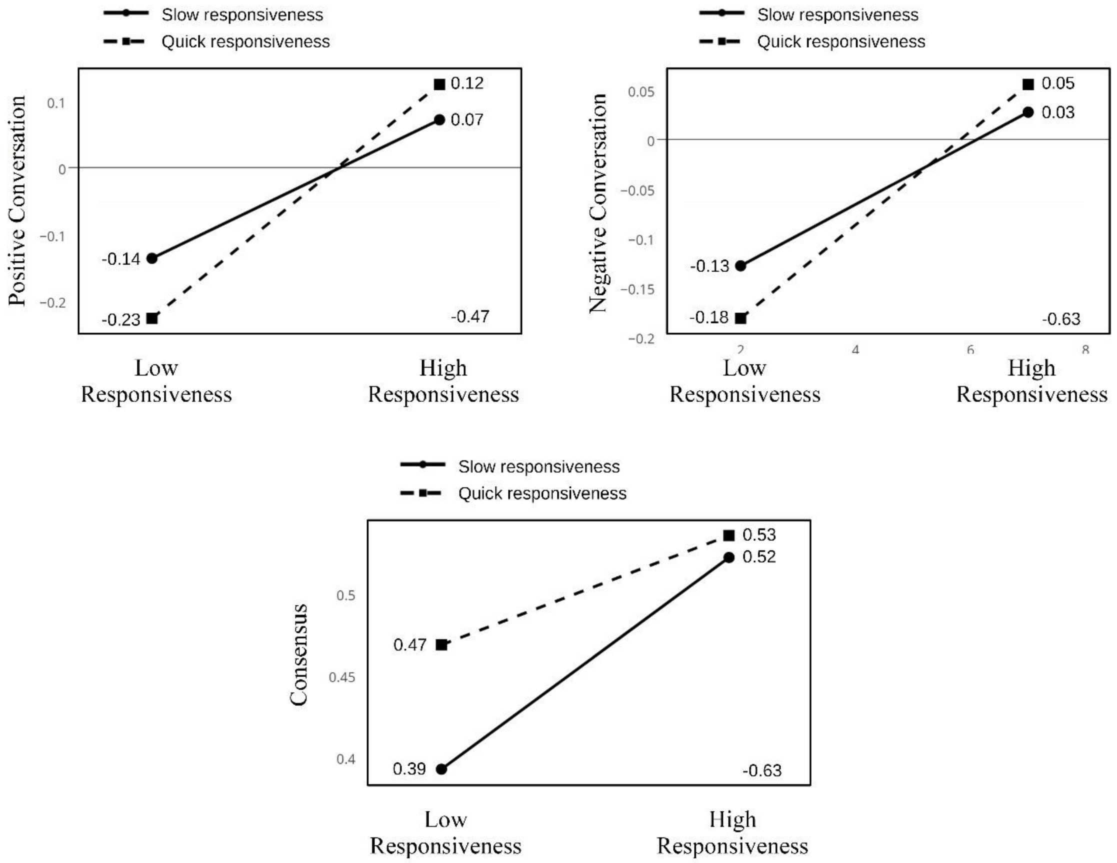


Figure 2. Interaction effects of the frequency and quickness of brand responsiveness

When it comes to C2C interactions, consumer feedback behaviors are significantly and positively associated with consumer conversation behaviors, providing support for H6. Moreover, positive feedback is positively associated with both positive conversation (β=0.12, p<0.001) and negative conversation (β=0.08, p<0.001) such that the overall effect is stronger for positive conversation than negative conversation, in support of H6a. Likewise, negative feedback is positively associated with both negative conversation (β=0.18, p<0.001) and positive conversation (β=0.16, p<0.001) such that the overall effect is slightly stronger for negative conversation than positive conversation, again in support of hypothesis H6a. Furthermore, the association between negative feedback and negative conversation (β=0.18, p<0.001) is stronger than the association between positive feedback and positive conversation (β=0.12, p<0.001), in support to H6b.

We also note that positive feedback (β=0.48, p<0.001) and negative feedback (β=0.35,

$p<0.001$) have a stronger relationship with consensus than positive conversation ($\beta=0.08$, $p<0.001$) and negative conversation ($\beta=0.06$, $p<0.001$) providing support for H7. H8 predicts an interaction between consumer recommendation and negative feedback behaviors affecting both positive and negative conversation. Table 8 shows a positive and significant interaction between recommendation and negative feedback for both positive conversation ($\beta=0.21$, $p<0.001$) and negative conversation ($\beta=0.29$, $p<0.001$). These interactions are visually depicted in Figure 3, indicating that both positive and negative conversations increase when recommendation is high and feedback is highly negative, in support to H8.

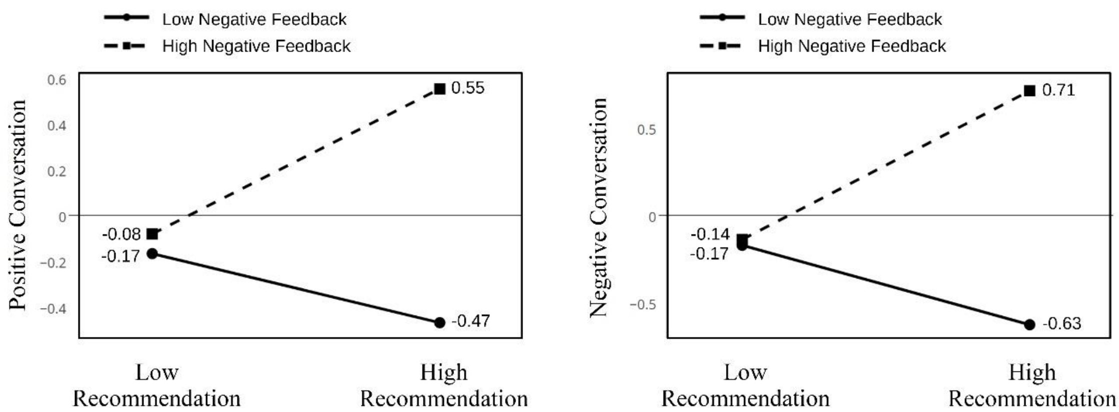


Figure 3. Interaction effects of recommendation and negative feedback

Discussion

Broadly speaking, this study points to the importance of effectively measuring CBE behaviors on social media and sheds light on the dynamic interplay between BEBs and CEBs. Our research focus is in line with calls for further work in measuring CBE behaviors on social media (Schivinski, Christodoulides and Dabrowski 2016). Guided by previous theory and research as well as a thorough analysis of the nature of CBE behaviors and the processes by which they occur on Facebook brand pages, we identify deficiencies of current measurement of online CBE behaviors and develop a single, integrative model to examine BEBs, CEBs, and their intricacies. This study provides insights into the factors contributing to consumer engagement on Facebook brand pages and contributes to existing academic research and industry practices in several ways.

While established marketing research demonstrates that BEBs drive CEBs, this study further underscores the distinct effects of brand presence and brand responsiveness on CEBs. The results indicate that frequently posting brand content is beneficial to brand exposure and visibility especially through increased endorsements, recommendations and to a lesser extent through feedback. To bolster consumer conversation and consensus, brand responsiveness in the form of frequent and timely brand replies is key. The effect of brand responsiveness on conversation and consensus is arguably related to Facebook's ranking algorithm that elevates the most relevant consumer feedback in the form of comments to the top of the thread. Consumer comments that generates a significant number of replies or/and likes, either from the brand or other consumers, would appear on the forefront of the brand post, increasing their visibility. As brand replies outweigh consumer replies in the ranking algorithm, brand responsiveness to positive (negative) consumer feedback likely drives their ranking up, triggering further positive (negative) conversation. Yet, our findings suggest that brand responsiveness has an overall beneficial effect as it contributes to increase more positive conversation than negative.

When considering the various formats of brand posts, vivid formats (photos and videos) positively moderate the relationship between brand presence and CEBs in C2B context. This finding demonstrates that vivid content boosts CEBs suggesting consumers are in search of more vivid and interactive content that captures and holds their attention. Compared to links and text formats, photos have the strongest positive moderating effect, more than twice as much as video. This is notable given that Facebook exceeded 8 billion video views per day back in 2015 and online video content is on the rise and predicted to drive more than 82% of the global search traffic by 2021 (CISCO 2017). While video posts generate more CEBs than links or text posts, they still do not match photos. This may be due to the expansion of social media on mobile platforms, which are constrained by internet bandwidth and data quotas. For all these reasons, Facebook users on mobile platforms tend to limit their access to rich and bandwidth demanding content, particularly video posts.

The timing of brand posts in this study has no significant effect. A possible explanation is related to the non-real time interactions between consumers and brands on Facebook brand pages. Perhaps, if brands take advantage of live video chat to reach consumers when they are online, they may be more effective in generating real-time conversations. Our findings demonstrate that the effect of negative feedback on negative conversation is stronger than the effect of positive feedback on positive conversation. Scholars argue that the highly contagious nature of social networks can serve as a hotbed for online firestorms (Pfeffer, Zorbach and Carley 2013), leading to a cascade of negative comments within a short period of time. Indeed, our results indicate that highly recommended posts with high levels of negative consumer feedback are associated with increased negative consumer conversations; however, our results also show that the same circumstances can led to increased positive consumer conversations. To the best of our knowledge, this is the first study to empirically demonstrate such effect.

Managerial implications

From a managerial standpoint, the research findings provide several actionable insights and recommendations to assist brand marketers in designing and implementing effective social media marketing strategies. First, and perhaps most importantly, our conceptual model enables marketing managers to examine the state of engagement on Facebook brand pages between the brand and its consumers and among consumers themselves. Implicit in this model is the idea that we must consider not only consumers' reactions (endorsement, recommendation and feedback) to the brand's engagement activities (brand presence and responsiveness), but also consumers' reactions to one another (conversation and consensus).

Second, the findings suggest that frequent brand posting positively impacts CEBs, but that effect is moderated by the media format of brand posts. We suggest that marketing managers should pay particular attention to visual posts, either photos or videos, and be careful not to inundate consumers with links or text based posts. Instead, they should aim for a balance of reasonable posting frequency allowing them to allocate enough resources to invest into prompt and frequent brand responsiveness to consumer comments. Nonetheless, the effect of brand responsiveness on consumer engagement is more complex than previously thought. Although brand responsiveness increases nearly equally positive feedback and negative feedback, it has a much more favorable effect on consumer conversation, increasing positive conversation to a greater extent than negative conversation. Marketing managers should be cautious not to respond to all negative comments in a single top level comment. An alternative strategy is to adopt a targeted approach and respond to specific negative consumer comments separately, which has been demonstrated to generate more positive conversations than negative ones.

The findings also suggest that the combination of high consumer recommendation with high levels of negative feedback increases both positive and negative consumer conversations. Therefore, we urge practitioners to monitor consumer discussions and let consumers defend the brand and act as the primary buffer against negative feedback when brand posts are not yet highly recommended, but to step in before a firestorm takes hold when brand posts become viral. This would free up brand marketers to prioritize brand responsiveness to negative feedback in the case of high recommendation posts.

Limitations and further research

As with all research, this study contains some limitations and many noteworthy issues are left unanswered that can be the focus of future research. First, the measurement of CBE discussed in the current research has been tailored to Facebook brand pages. Therefore, caution is warranted in generalizing the findings to other online social media platforms such as Twitter, Google+, LinkedIn or Tumblr. While most Facebook CBE behaviors discussed in this paper have their equivalent in other social media platforms, they often have different names (e.g. Google's +1 is the equivalent of Facebook's Like) and potentially can be measured in new ways revealing additional CBE constructs or refinements of the existing ones for each social media platform.

Secondly, this research does not take into account CBE behaviors involving real-time interactions between brands and consumers on Facebook due to the lack of uptake, at the time of data collection. Recently, Facebook has introduced Chatbots on Messenger to provide personalized attention to consumers at scale and encourage brand managers to interact in real-time with consumers. An examination of the contribution of Facebook Messenger and Chatbots to CBE on Facebook is a fruitful area of future study.

Thirdly, whilst this study is based on over 12 months' worth of data, CBE dynamics over time is not explored. Capturing CBE dynamics over time is of critical importance. To do so, a longitudinal analysis using either time series or latent growth curve analysis (Bijleveld et al. 1998) will shed light on potential CBE phases or cycles by describing patterns of change. Future work can also concentrate on the causality, rather than correlation, between CBE constructs, such as the effect of brand replies or the sharing behavior on subsequent consumer feedback and conversation. Finally, limited academic research examines the phenomenon of consumer brand disengagement/re-engagement on social media, which is a rich area worth investigating.

References

Adjei, Mavis T., Stephanie M. Noble, and Charles H. Noble. (2010), "The influence of C2C communications in online brand communities on customer purchase behavior." *Journal of the Academy of Marketing Science*, 38, 5, 634-653.

Ahluwalia, Rohini. (2002), "How prevalent is the negativity effect in consumer environments?" *Journal of consumer research*, 29, 2, 270-279.

Aiken, Leona S., Stephen G. West, and Raymond R. Reno. (1991), *Multiple regression: Testing and interpreting interactions*. Sage.

Allsop, Dee T., Bryce R. Bassett, and James A. Hoskins. (2007), "Word-of-mouth research: principles and applications." *Journal of advertising research*, 47, 4, 398-411.

Ambler, Tim, and John H. Roberts. (2008), "Assessing marketing performance: don't settle for a silver metric." *Journal of Marketing Management*, 24, 7-8, 733-750.

Ashley, Christy, and Tracy Tuten. (2015), "Creative strategies in social media marketing: An exploratory study of branded social content and consumer engagement." *Psychology & Marketing*, 32, 1, 15-27.

Ashley, Christy, Stephanie M. Noble, Naveen Donthu, and Katherine N. Lemon. (2011), "Why customers won't relate: Obstacles to relationship marketing engagement." *Journal of Business Research*, 64, 7, 749-756.

Barker, Paris. (2008), "How social media is transforming employee communications at Sun Microsystems." *Global Business and Organizational Excellence*, 27, 4, 6-14.

Bates, Douglas, Martin Maechler, Ben Bolker, and Steven Walker. (2014), "lme4: Linear mixed-effects models using Eigen and S4." *R package version*, 1, 7, 1-23.

Berger, Jonah A., and Chip Heath. (2005), "Idea habitats: How the prevalence of environmental cues influences the success of ideas." *Cognitive Science*, 29, 2, 195-221.

Berger, Jonah, Alan T. Sorensen, and Scott J. Rasmussen. (2010), "Positive effects of negative publicity: When negative reviews increase sales." *Marketing Science*, 29, 5, 815-827.

Berger, Jonah, and Katherine L. Milkman. (2012), "What makes online content viral?" *Journal of marketing research*, 49, 2, 192-205.

Berger, Jonah. (2014), "Word of mouth and interpersonal communication: A review and directions for future research." *Journal of Consumer Psychology*, 24, 4, 586-607.

Bijleveld, Catrien CJHCJH, J. Th Leo, J. Leo, Ab Mooijaart, Willem A. Van Der Van Der, Rien Van Der Leeden, and Eeke Van Der Burg. (1998), *Longitudinal data analysis: Designs, models and methods*. Sage.

Blau, Peter Michael. (1964), *Exchange and power in social life*. Transaction Publishers.

Bolton, Ruth N. (2011), "Comment: Customer engagement: Opportunities and challenges for organizations." *Journal of Service Research*, 14, 3, 272-274.

Bowden, Jana Lay-Hwa. (2009), "The process of customer engagement: A conceptual framework." *Journal of Marketing Theory and Practice*, 17, 1, 63-74.

Boyd, Danah M., and Nicole B. Ellison. (2007), "Social Network Sites: Definition, History, and Scholarship." *Journal of computer‐mediated communication*, 13, 1, 210-230.

Brodie, Roderick J., Ana Ilic, Biljana Juric, and Linda Hollebeek. (2013), "Consumer engagement in a virtual brand community: An exploratory analysis." *Journal of Business Research*, 66, 1, 105-114.

Brodie, Roderick J., Linda D. Hollebeek, Biljana Jurić, and Ana Ilić. (2011), "Customer engagement: Conceptual domain, fundamental propositions, and implications for research." *Journal of Service Research*, 14, 3, 252-271.

Calder, Bobby J., Edward C. Malthouse, and Ewa Maslowska. (2016), "Brand marketing, big data and social innovation as future research directions for engagement." *Journal of Marketing Management*, 32, 5-6, 579-585.

Calder, Bobby J., Edward C. Malthouse, and Ute Schaedel. (2009), "An experimental study of the relationship between online engagement and advertising effectiveness." *Journal of Interactive Marketing*, 23, 4, 321-331.

Chan, Kimmy Wa, and Stella Yiyan Li. (2010), "Understanding consumer-to-consumer interactions in virtual communities: The salience of reciprocity." *Journal of Business Research*, 63, 9, 1033-1040.

Chauhan, Kalpana, and Anandan Pillai. (2013), "Role of content strategy in social media brand communities: a case of higher education institutes in India." *Journal of Product & Brand Management*, 22, 1, 40-51.

Chen, Zoey, and Nicholas H. Lurie. (2013), "Temporal contiguity and negativity bias in the impact of online word of mouth." *Journal of Marketing Research* 50, 4, 463-476.

Chevalier, Judith A., and Dina Mayzlin. (2006), "The effect of word of mouth on sales: Online book reviews." *Journal of marketing research*, 43, 3, 345-354.

Chib, Siddhartha, and Edward Greenberg. (1995), "Hierarchical analysis of SUR models with extensions to correlated serial errors and time-varying parameter models." *Journal of Econometrics*, 68, 2, 339-360.

Chiou, Jyh-Shen, and Cathy Cheng. (2003), "Should a company have message boards on its web sites?" *Journal of Interactive Marketing*, 17, 3, 50-61.

Choi, Jihyang, and Jae Kook Lee. (2015), "Investigating the effects of news sharing and political interest on social media network heterogeneity." *Computers in Human Behavior*, 44, 258-266.

Choudhury, Musfiq Mannan, and Paul Harrigan. (2014), "CRM to social CRM: the integration of new technologies into customer relationship management." *Journal of Strategic Marketing*, 22, 2, 149-176.

Chung, Cindy MY, and Peter R. Darke. (2006), "The consumer as advocate: Self-relevance, culture, and word-of-mouth." *Marketing Letters*, 17, 4, 269-279.

CISCO (2017), *The Zettabyte Era: Trends and Analysis*, Accessible at https://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/vni-hyperconnectivity-wp.html

Coyle, James R., and Esther Thorson. (2001), "The effects of progressive levels of interactivity and vividness in web marketing sites." *Journal of advertising*, 30, 3, 65-77.

Cvijikj, Irena Pletikosa, and Florian Michahelles. (2013), "Online engagement factors on Facebook brand pages." *Social Network Analysis and Mining*, 3, 4, 843-861.

Daugherty, Terry, Matthew S. Eastin, and Laura Bright. (2008), "Exploring consumer motivations for creating user-generated content." *Journal of Interactive Advertising*, 8, 2, 16-25.

De Vries, Lisette, Sonja Gensler, and Peter SH Leeflang. (2012), "Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing." *Journal of interactive marketing*, 26, 2, 83-91.

De Vries, Natalie Jane, and Jamie Carlson. (2014), "Examining the drivers and brand performance implications of customer engagement with brands in the social media environment." *Journal of Brand Management* 21, 6, 495-515.

Dellarocas, Chrysanthos, Guodong Gao, and Ritu Narayan. (2010), "Are consumers more likely to contribute online reviews for hit or niche products?" *Journal of Management Information Systems*, 27, 2, 127-158.

Dessart, Laurence, Cleopatra Veloutsou, and Anna Morgan-Thomas. (2016), "Capturing consumer engagement: duality, dimensionality and measurement." *Journal of Marketing Management*, 32, 5-6, 399-426.

Donaldson, Stewart I., and Elisa J. Grant-Vallone. (2002), "Understanding self-report bias in organizational behavior research." *Journal of business and Psychology*, 17, 2, 245-260.

East, Robert, Kathy Hammond, and Wendy Lomax. (2008), "Measuring the impact of positive and negative word of mouth on brand purchase probability." *International journal of research in marketing* 25, 3, 215-224.

Ein-Gar, Danit, Jacob Goldenberg, and Lilach Sagiv. (2012), "The role of consumer self-control in the consumption of virtue products." *International Journal of Research in Marketing* 29, 2, 123-133.

Evans, Liana. (2010), *Social media marketing: strategies for engaging in Facebook, Twitter & other social media*. Pearson Education.

Ferrara, Emilio, and Zeyao Yang. (2015), "Measuring emotional contagion in social media." *PloS one* 10, 11, e0142390.

Fournier, Susan, and Jill Avery. (2011), "The uninvited brand." *Business horizons*, 54, 3, 193-207.

France, Cassandra, Bill Merrilees, and Dale Miller. (2016), "An integrated model of customer-brand engagement: Drivers and consequences." *Journal of Brand Management*, 23, 2, 119-136.

Fulgoni, Gian M. (2016), "In the digital world, not everything that can be measured matters." *Journal of Advertising Research*, 56, 1, 9-13.

Garber Jr, Lawrence L., Eva M. Hyatt, and Ünal Ö. Boya. (2009), "The Collaborative Roles of the Designer, the Marketer, and the Consumer in Determining What Is Good Design." *Advertising & Society Review*, 10, 1.

Gensler, Sonja, Franziska Völckner, Yuping Liu-Thompkins, and Caroline Wiertz. (2013), "Managing brands in the social media environment." *Journal of Interactive Marketing*, 27, 4, 242-256.

Gummerus, Johanna, Veronica Liljander, Emil Weman, and Minna Pihlström. (2012), "Customer engagement in a Facebook brand community." *Management Research Review*, 35, 9, 857-877.

Hair, Joseph F., William C. Black, Barry J. Babin, Rolph E. Anderson, and Ronald L. Tatham. (1998), *Multivariate data analysis*. Vol. 5, no. 3. Upper Saddle River, NJ: Prentice hall.

Hartmann, Benjamin J., Caroline Wiertz, and Eric J. Arnould. (2015), "Exploring consumptive moments of value-creating practice in online community." *Psychology & Marketing*, 32, 3, 319-340.

Heath, Chip, Chris Bell, and Emily Sternberg. (2001), "Emotional selection in memes: the case of urban legends." *Journal of personality and social psychology*, 81, 6, 1028.

Hennig-Thurau, Thorsten, Edward C. Malthouse, Christian Friege, Sonja Gensler, Lara Lobschat, Arvind Rangaswamy, and Bernd Skiera. (2010), "The impact of new media on customer relationships." *Journal of service research*, 13, 3, 311-330.

Hollebeek, Linda D. (2011a), "Demystifying customer brand engagement: Exploring the loyalty nexus." *Journal of marketing management*, 27, 7-8, 785-807.

Hollebeek, Linda. (2011b), "Exploring customer brand engagement: definition and themes." *Journal of* *strategic Marketing*, 19, 7, 555-573.

Hollebeek, Linda D., Mark S. Glynn, and Roderick J. Brodie. (2014), "Consumer brand engagement in social media: Conceptualization, scale development and validation." *Journal of interactive marketing*, 28, 2, 149-165.

Homburg, Christian, Laura Ehm, and Martin Artz. (2015), "Measuring and Managing Consumer Sentiment in an Online Community Environment." *Journal of Marketing Research*, 52, 5, 629-641.

Hong, Ji-Young, and Wei-Na Lee. (2005), "Consumer complaint behavior in the online environment." *Web systems design and online consumer behavior*, New Jersey 2005 (2005): 90-105.

Ito, Tiffany A., Jeff T. Larsen, N. Kyle Smith, and John T. Cacioppo. (1998), "Negative information weighs more heavily on the brain: the negativity bias in evaluative categorizations." *Journal of personality and social psychology*, 75, 4, 887.

Jaakkola, Elina, and Matthew Alexander. (2014), "The role of customer engagement behavior in value co-creation: a service system perspective." *Journal of Service Research* 17, 3, 247-261.

Jahn, Benedikt, and Werner Kunz. (2012), "How to transform consumers into fans of your brand." *Journal of Service Management* 23, 3, 344-361.

Kabadayi, Sertan, and Katherine Price. (2014), "Consumer–brand engagement on Facebook: liking and commenting behaviors." *Journal of Research in Interactive Marketing* 8, 3, 203-223.

Karpen, Ingo O., Liliana L. Bove, and Bryan A. Lukas. (2012), "Linking service-dominant logic and strategic business practice: A conceptual model of a service-dominant orientation." *Journal of Service Research*, 15, 1, 21-38.

Kozinets, Robert V., Kristine De Valck, Andrea C. Wojnicki, and Sarah JS Wilner. (2010), "Networked narratives: Understanding word-of-mouth marketing in online communities." *Journal of marketing*, 74, 2, 71-89.

Kumar, Subodha, Varghese S. Jacob, and Chelliah Sriskandarajah. (2006), "Scheduling advertisements on a web page to maximize revenue." *European journal of operational research*, 173, 3, 1067-1089.

Lamberton, Cait, and Andrew T. Stephen. (2016), "A thematic exploration of digital, social media, and mobile marketing: research evolution from 2000 to 2015 and an agenda for future inquiry." *Journal of Marketing* 80, 6, 146-172.

Leckie, Civilai, Munyaradzi W. Nyadzayo, and Lester W. Johnson. (2016), "Antecedents of consumer brand engagement and brand loyalty." *Journal of Marketing Management*, 32, 5-6, 558-578.

Macnamara, Jim. (2014)**,** "Emerging international standards for measurement and evaluation of public relations: A critical analysis." *Public Relations Inquiry*, 3, 1, 7-29.

Mangold, W. Glynn, and David J. Faulds. (2009), "Social media: The new hybrid element of the promotion mix." *Business horizons,* 52, 4, 357-365.

Maslowska, Ewa, Edward C. Malthouse, and Tom Collinger. (2016), "The customer engagement ecosystem." *Journal of Marketing Management*, 32, 5-6, 469-501.

Menard, Scott. (1995), *Applied logistic regression analysis*. Sage university series on quantitative applications in the social sciences.

Meng, Qingguo, Nan Zhang, Xuejiao Zhao, Fangling Li, and Xin Guan. (2016), "The governance strategies for public emergencies on social media and their effects: a case study based on the microblog data." *Electronic Markets*, 26, 1, 15-29.

Merrilees, Bill, and Marie-Louise Fry. (2003), "E-trust: the influence of perceived interactivity on e-retailing users." *Marketing Intelligence & Planning*, 21, 2, 123-128.

Miller, Amalia R., and Catherine Tucker. (2013), "Active social media management: the case of health care." *Information Systems Research*, 24, 1, 52-70.

Mollen, Anne, and Hugh Wilson. (2010), "Engagement, telepresence and interactivity in online consumer experience: Reconciling scholastic and managerial perspectives." *Journal of business research*, 63, 9, 919-925.

Mousavi, Sahar, Stuart Roper, and Kathleen A. Keeling. (2017), "Interpreting social identity in online brand communities: Considering posters and lurkers." *Psychology & Marketing*, 34, 4, 376-393.

MSI (2010), 2010-2012 *Research Priorities*. Boston, MA: Marketing Science Institute.

Oviedo-García, Mª Ángeles, Miriam Muñoz-Expósito, Mario Castellanos-Verdugo, and María Sancho-Mejías. (2014), "Metric proposal for customer engagement in Facebook." *Journal of Research in Interactive Marketing*, 8, 4, 327.

Pennebaker, James W., Ryan L. Boyd, Kayla Jordan, and Kate Blackburn. (2015), *The development and psychometric properties of LIWC2015*. Technical report, University of Texas at Austin.

Peppler, Kylie A., and Maria Solomou. (2011), "Building creativity: Collaborative learning and creativity in social media environments." *On the Horizon*, 19, 1, 13-23.

Peters, Kay, Yubo Chen, Andreas M. Kaplan, Björn Ognibeni, and Koen Pauwels. (2013), "Social media metrics—A framework and guidelines for managing social media." *Journal of interactive marketing*, 27, 4, 281-298.

Pfeffer, Jürgen, Thomas Zorbach, and Kathleen M. Carley. (2014), "Understanding online firestorms: Negative word-of-mouth dynamics in social media networks." *Journal of Marketing Communications*, 20, 1-2, 117-128.

Pratto, Felicia, and Oliver P. John. (1991), "Automatic Vigilance: The Attention-Grabbing Power of negative Social Information." *Journal of Personality and Social Psychology*, 61, 3, 380-91.

Precourt, Geoffrey. (2016), "How is consumer engagement reshaping marketing?" *Journal of Advertising Research*, 56, 1, 2-3.

Relling, Marleen, Oliver Schnittka, Henrik Sattler, and Marius Johnen. (2016), "Each can help or hurt: Negative and positive word of mouth in social network brand communities." *International Journal of Research in Marketing* 33, 1, 42-58.

Sabate, Ferran, Jasmina Berbegal-Mirabent, Antonio Cañabate, and Philipp R. Lebherz. (2014), "Factors influencing popularity of branded content in Facebook fan pages." *European Management Journal*, 32, 6, 1001-1011.

Sawhney, Mohanbir, Gianmario Verona, and Emanuela Prandelli. (2005), "Collaborating to create: The Internet as a platform for customer engagement in product innovation." *Journal of interactive marketing*, 19, 4, 4-17.

Schamari, Julia, and Tobias Schaefers. (2015), "Leaving the home turf: how brands can use webcare on consumer-generated platforms to increase positive consumer engagement." *Journal of Interactive Marketing*, 30, 20-33.

Schivinski, Bruno, George Christodoulides, and Dariusz Dabrowski. (2016), "Measuring Consumers' Engagement With Brand-Related Social-Media Content." *Journal of Advertising Research*, 56, 1, 64-80.

Schlosser, Ann E. (2005), "Source perceptions and the persuasiveness of internet word-of-mouth communication." *ACR North American Advances*.

Schultz, Don E., Bill Cole, and Scott Bailey. (2004), "Implementing the 'connect the dots' approach to marketing communication." *International Journal of Advertising*, 23, 4, 455-477.

Schulze, Christian, Lisa Schöler, and Bernd Skiera. (2014), "Not all fun and games: Viral marketing for utilitarian products." *Journal of Marketing*, 78, 1, 1-19.

Sensis (2015), *Social Media Report May 2015 - How Australian people and businesses are using social media.*

Seraj, Mina. (2012), "We create, we connect, we respect, therefore we are: intellectual, social, and cultural value in online communities." *Journal of Interactive Marketing*, 26, 4, 209-222.

Sherman, David K., and Geoffrey L. Cohen. (2006), "The psychology of self-defense: Self-affirmation theory." *Advances in experimental social psychology*, 38, 183-242.

Shrum, Larry J. (2002), "Media consumption and perceptions of social reality: Effects and underlying processes." *Media effects: Advances in theory and research*, 2, 69-95.

Tausczik, Yla R., and James W. Pennebaker. (2010), "The psychological meaning of words: LIWC and computerized text analysis methods." *Journal of language and social psychology*, 29, 1, 24-54.

Taylor, Charles R. (2010), "Measuring return on investment from advertising: 'holy grail' or necessary tool?" *International Journal of Advertising*, 29, 3, 345-348.

United Nations Statistics Division. (2008), International Standard Industrial Classification of All Economic Activities (ISIC), Revision 4. United Nations, New York.

van Doorn, Jenny, Katherine N. Lemon, Vikas Mittal, Stephan Nass, Doreén Pick, Peter Pirner, and Peter C. Verhoef. (2010), "Customer engagement behavior: Theoretical foundations and research directions." *Journal of service research*, 13, 3, 253-266.

van Laer, Tom, and Ko De Ruyter. (2010), "In stories we trust: How narrative apologies provide cover for competitive vulnerability after integrity-violating blog posts." *International Journal of Research in Marketing*, 27, 2, 164-174.

van Noort, Guda, and Lotte M. Willemsen. (2012), "Online damage control: The effects of proactive versus reactive webcare interventions in consumer-generated and brand-generated platforms." *Journal of Interactive Marketing*, 26, 3, 131-140.

Vargo, Stephen L., and Robert F. Lusch. (2004), "Evolving to a new dominant logic for marketing." *Journal of marketing*, 68, 1, 1-17.

Vargo, Stephen L., and Robert F. Lusch. (2008), "Service-dominant logic: continuing the evolution." *Journal of the Academy of marketing Science*, 36, 1, 1-10.

Vincent, Nathan A., and Cynthia M. Webster. (2013), "Exploring relationship marketing in membership associations." *European Journal of Marketing*, 47, 10, 1622-1640.

Vivek, Shiri D., Sharon E. Beatty, and Robert M. Morgan. (2012), "Customer engagement: Exploring customer relationships beyond purchase." *Journal of Marketing Theory and Practice*, 20, 2, 122-146.

Wallace, Elaine, Isabel Buil, and Leslie de Chernatony. (2014), "Consumer engagement with self-expressive brands: brand love and WOM outcomes." *Journal of Product & Brand Management*, 23, 1, 33-42.

Wilson, Andrew E., Michael D. Giebelhausen, and Michael K. Brady. (2017), "Negative word of mouth can be a positive for consumers connected to the brand." *Journal of the Academy of Marketing Science*, 45, 4, 534-547.

Wolny, Julia, and Claudia Mueller. (2013), "Analysis of fashion consumers' motives to engage in electronic word-of-mouth communication through social media platforms." *Journal of Marketing Management*, 29, 5-6, 562-583.

Yang, Shuai, Shan Lin, Jeffrey R. Carlson, and William T. Ross Jr. (2016), "Brand engagement on social media: will firms' social media efforts influence search engine advertising effectiveness?" *Journal of Marketing Management* 32, 5-6, 526-557.

Zellner, Arnold. (1962), "An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias." *Journal of the American statistical Association* 57, 298, 348-368.

Conclusion to paper I

The first paper of the thesis contributes to existing academic research and industry practices in several ways. First, this paper helps identify deficiencies of current measurement models of engagement and develop a single, integrative model to examine BEBs, CEBs, and their intricacies. Second, this paper provides insights into the factors contributing to consumer engagement on Facebook brand pages. The results indicate that frequently posting brand content is beneficial to brand exposure and visibility especially through increased endorsements, recommendations and to a lesser extent through feedback. The results also show that brand responsiveness in the form of frequent and timely brand replies to consumer comments has an overall beneficial effect as it contributes to increase more positive conversations than negative ones. When considering the formats of brand posts, the results demonstrate that vivid content, particularly images and videos, boost CEBs suggesting that consumers are in search of more vivid and interactive content that captures and holds their attention. Finally, the findings suggest that consumers strongly influence each other and that negative consumer feedback is more influential than positive feedback on consumer conversations. From a managerial standpoint, the research findings provide actionable insights and recommendations to assist brand marketers in designing and implementing effective social media marketing strategies to increase consumer engagement behaviors.

While the first paper provides key insights into the behavioral perspective of consumer brand engagement, the second paper extends it to the emotional perspective and draws on the emotional branding and emotional contagion research to further our understanding of the emotional dynamics that take place on Facebook brand pages. As paper I highlights the importance of adequate measurement of consumer brand engagement and provide insights on the intricacies of brand engagement behaviors and consumer engagement behaviors, paper II explores the effects of webcare interventions (brand replies) in consumer-to-consumer conversations in more details driven by the need to mitigate negative conversations and bolster positive ones.

Chapter 3: Introduction to paper II

The second paper in the thesis, entitled "Webcare Interventions in Consumer-to-Consumer Conversations: An Empirical Investigation on Facebook Brand Pages", is an empirical research examining the effects of webcare interventions in consumer-to-consumer conversations on Facebook brand pages. A large dataset of 64,347 webcare interventions embedded within 24,557 consumer conversations is analyzed to determine whether type (proactive versus reactive), voice (personal versus impersonal), timing (early versus late) and number (single versus multiple) of webcare interventions influence the volume and valence of consumer conversations.

Webcare Interventions in Consumer-to-Consumer Conversations: An Empirical Investigation on Facebook Brand Pages is targeted for submission to the Journal of Interactive Marketing. The paper is presented in this thesis in the journal's required publication format yet for ease of reading tables and figures are embedded throughout. This study evolved from a paper presented at the Winter AMA Conference, 2017. The conference paper is authored by Chedia Dhaoui, Cynthia M. Webster and LayPeng Tan with the contribution ratio as the thesis paper (outlined in the Acknowledgments section) and is included in Appendix A.

Webcare interventions in consumer-to-consumer conversations: An empirical investigation on Facebook Brand Pages

Chedia Dhaoui, Macquarie University, Australia, chedia.dhaoui@mq.edu.au

Cynthia M. Webster, Macquarie University, Australia, cynthia.webster@mq.edu.au

LayPeng Tan, Macquarie University, Australia, laypeng.tan@mq.edu.au

Abstract.

This paper examines 2,740 Facebook brand pages to gain a deeper understanding of how webcare affects consumer-to-consumer conversations over time. A large dataset collected from Facebook brand pages across 25 industry sectors consisting of 64,347 webcare interventions embedded within 24,557 consumer conversations is used to determine whether the type of webcare intervention, the timing, the promptness and whether multiple interventions influence the volume and valence of consumer conversations. Results show that brands conduct webcare interventions mostly in consumer conversations with a higher volume of consumer comments and a slightly higher proportion of negative comments. The effects of webcare interventions on the volume and valence of consumer comments are found to vary depending on whether webcare interventions are reactive or proactive, single or multiple, personal or impersonal, early or late in the conversation, and prompt or delayed when responding to a consumer comment. The research also shed light on how these characteristics of webcare interventions interact to bolster favorable outcomes. The findings provide an empirical evaluation of webcare strategies identifying crucial factors brand managers should consider in the design, monitoring and management of online consumer conversations surrounding their brands on Facebook.

Keywords: Consumer conversations; Webcare interventions; Big data; Facebook brand pages.

Introduction

In today's highly connected environment, consumer-to-consumer interactivity is one of the most groundbreaking effects of digital social media marketing (Lamberton and Stephen 2016). Brand managers, striving to keep close relationships with their valuable consumers, have a keen interest to engage with online brand communities. Indeed, the widespread adoption of social media along with the increasing use of Internet connected mobile smartphones have opened for consumers new exciting communication channels to actively create and disseminate content as well as influence others. In this regard, Lamberton and Stephen (2016) emphasize that consumers are “not only connected but also empowered by their online connections to others” (p.159) making them more than contributors and disseminators of online brand related content, “but rather agents who could amplify or undermine the effect of marketing actions” (p.159).

While the advent of social media has provided brand managers a great potential to take advantage of unfettered consumer generated data for marketing decision making, practitioners remain concerned about the challenges in managing online consumer conversations, particularly when conversations turn from positive to negative leading often to detrimental effects. Fueling the contagion or spillover of negative online chatter, consumers not only voice their complaints but also take part in online revenge and sabotage behaviors by spreading hate messages and actively calling for boycotts (Klein et al 2004; Berry et al 2010; McColl-Kennedy, Sparks and Nguyen 2011). Such actions potentially can cause damage to a brand's reputation which can take substantial investment of time and resources to recover. Consequently, brand managers engage in webcare strategies to intervene in consumer conversations in order to circumvent or mitigate negative online interactions between consumers and to leverage positive consumer sentiment (Fournier and Avery 2011; Hennig-Thurau et al 2010; Vivek, Beatty and Morgan 2012).

Prior research shows webcare as an effective brand intervention strategy to counter the effects of negative electronic word-of-mouth (van Noort and Willemsen 2012) and increase positive brand-related consumer engagement (Schamari and Schaefers 2015). Although they have provided meaningful insights into online webcare, to date, much of the academic research relies on observations from experimental settings, focusing on a single webcare intervention at a specific point in time. Furthermore, to the best of our knowledge, no previous studies so far have examined the dynamics of actual webcare interventions in online consumer conversations entailing both positive and negative consumer comments. As such, it remains unclear how consumers within real-world situations would react to multiple successive webcare interventions within the same conversation.

Based on a large dataset of consumer conversations on Facebook brand pages, we contribute further insights into the dynamics of webcare interventions and their effects on consumer conversations. This research addresses three managerially relevant research questions: 1) To what extent do webcare interventions affect online consumer conversations? 2) What are the mechanisms underpinning effective webcare strategies to foster positive consumer conversations and mitigate negative ones? 3) What are the effects of timing and frequency of webcare interventions on consumer conversations?

Conceptual Background and Hypotheses

With the remarkable development of online social networks, brand managers have had to rethink the way they engage with brand communities on social media platforms. Empowered by new communication technologies, consumers are now actively involved in many-to-many communications with brands as well as other consumers (Hoffman and Novak 2011; Lamberton and Stephen 2016). Instead of merely consuming brand related information, consumers these days are able to co-create and exchange brand related content (Kaplan and Haenlein 2010, Muntinga, Moorman, and Smit 2011). They come together in online communities and on Facebook brand pages to share their brand-related thoughts and sentiment by commenting on brand posts and replying to other consumer comments, shaping consumer conversations.

Facebook brand pages are interactive social platforms that facilitate online consumer conversations and enable firms to get involved in the conversations by replying to consumer comments and interacting with consumers directly and transparently (Dellarocas 2003; 2006). We consider webcare interventions in consumer conversations on Facebook brand pages as discrete events generated by the brand in reply to consumer comments. Amid consumer conversations on Facebook, brands can either be passive by just observing consumer comments, or be an active actor by interacting with consumers and contributing to the conversation (Dholakia et al 2009; Shau, Muniz and Arnauled 2009). Brands can reply to specific consumer comments or take part in the conversation by posting proactive comments to the conversation, while consumers can further respond to webcare interventions. Monitoring and managing online consumer conversations has become a pivotal part of brand management (Schamari and Shaefers 2015). Negative consumer sentiment is found to have “detrimental effects on all phases of the consumer decision-making process” (van Noort and Willemsen 2012, p.131) whereas positive sentiment improves consumer attitude and leads to favorable behavior (Gummerus et al 2012; Seraj 2012; Brodie et al 2013). However, experimental evidence demonstrates that individuals, even when having a positive brand experience, are influenced more by other consumers’ negative online word-of-mouth (Schlosser 2005). Therefore, given that negative word-of-mouth is more influential than positive word-of-mouth, and that brands do not want to be perceived as intrusive, we expect webcare interventions to occur more frequently in negative conversations compared to positive conversations. Thus, the following hypothesis:

H1: Webcare interventions in consumer conversations on Facebook brand pages occur more frequently in negative consumer conversations than in positive consumer conversations.

The emergent research on the effects of webcare interventions on consumer conversations indicates favourable outcomes of webcare in terms of volume and valence. Since a conversation consists of a series of comments and replies to comments on a brand post, the volume of consumer comments captures the number of comments and replies to comments generated throughout the conversation while the valence of consumer comments indicates the proportion of positive (vs. negative) sentiment in the conversation. Experimental research indicates that webcare interventions are effective in mitigating negative consumer conversations and fostering positive ones. Previous research has established that webcare interventions are effective marketing strategies for mitigating the effects of online negative consumer conversations. For instance, van Noort and Willemsen (2012) have demonstrated that webcare intervention permit to attenuate negative brand evaluations. Also, van Laer and de Ruyter (2010) have found that brand responses to consumer blog posts help brand managers to attenuate the detrimental effects of negative consumer posts by restoring brand integrity and preventing consumers' switch. Webcare interventions are also effective in fostering online positive consumer conversations. For example, Schamari and Schaefers (2015) have found that webcare interventions directed at positive consumer comments about the brand function as a social reward for consumers and acknowledgment for their contributions which in turn increases consumers' engagement intentions. Based on this research, we expect webcare interventions on Facebook brand pages to have an effect on both the valence and volume of consumer conversations. This is formally stated in the following hypothesis:

H2. Webcare interventions in consumer conversations on Facebook brand pages impact a) the volume and b) the valence of subsequent consumer comments.

Recent work looks at different types of webcare strategies, such as proactive versus reactive, where reactive webcare interventions are those responding to specific consumer comments while proactive interventions are unsolicited posts introduced by the brand in consumer conversations. van Noort and Willemsen (2012) found that, in both consumer-generated and brand-generated platforms, reactive webcare interventions generate more positive brand evaluations. They also found that proactive webcare interventions results in more positive brand evaluations in brand-generated platforms than in consumer-generated platforms. As Facebook brand pages are fundamentally brand-generated platforms, created and managed by the brand, we propose the following hypothesis:

H3. Proactive (versus reactive) webcare interventions in consumer conversations on Facebook brand pages result in a) a larger volume of subsequent consumer comments that b) contain more positive and less negative valence.

Communicating in a conversational manner is considered as one of the most important aspects of online communication (Searls and Weinberger 2000). According to Sook and Juoyoung (2013), in online social media settings, consumers interact with brands as if they are viable communication partners rather than intangible entities. Academic research demonstrates that consumer perceptions of a brand's socialness positively contributes to change consumer attitudes (Wang et al 2007; Delbaere, McQuarrie and Phillips 2011). In addition, the humanlike features of a brand, reference to the brand by personal pronouns or mentioning it in the first (versus third) person increase brand liking (Aggrawal and McGill 2007; Landwehr, McGill and Herrmann 2011). In the same vein, Park and Cameron (2014) argue that the use of personal narratives and first-person voice improve perceptions of interactivity and social presence. Other studies exploring the effects of personal versus impersonal webcare on consumer-generated social media platforms (Schamari and Schaefers 2015) find that, compared to impersonal webcare interventions, personal webcare interventions are more effective in driving consumer engagement intentions.

Several more studies demonstrate that perceived conversational human voice in brand communications is positively related to high levels of interactivity between brands and consumers, and contributes to positive brand evaluations (van Noort and Willemsen 2012; van Noort et al 2014), positive attitudes toward the brand (Yang, Kang and Johnson 2010), favorable consumer reactions, such as positive emotions, positive experiences and product likability (Kelleher and Miller 2006; Wang et al 2007; Delbaere, McQuarrie and Phillips 2011). Therefore, we submit the following hypothesis:

H4. Personal (versus impersonal) webcare interventions in consumer conversations on Facebook brand pages result in a) a larger volume of subsequent consumer comments that b) contain more positive and less negative valence.

Research also examines the timing of a firm's webcare response to consumer conversations in online forums (Homburg, Ehm, and Artz 2015) and its effect on consumer sentiment. Although they did not find significant effect, other researchers have demonstrated that webcare timing contributes positively to counter-act negative (foster positive) consumer conversations. As pointed out by van Noort and Willemsen (2012), when brands respond to consumers' negative word-of-mouth in a timely manner, they demonstrate that they care about their consumers' issues (Hong and Lee 2005; van Laer and de Ruyter 2010). To handle consumers' complaints, Davidow (2000) has shown that the timeliness of managerial responses plays a key role in generating positive outcomes, including improved complaint's satisfaction and an increase in positive word-of-mouth.

Although webcare interventions in consumer-to-consumer conversations on social media does not always fit a crisis scenario, the crisis management literature has long recommended a prompt brand response to a crisis (Garbett 1988). Such recommendation is arguably valid for webcare in response to negative consumer comments. Moreover, Wirtz and Mattila (2004) have indicated that a quick recovery with apology following a service failure generates positive outcomes in terms of consumers' perception of controllability of the failure. More recently, Ghosh (2017) has examined the effect of webcare timeliness on negative online reviews following service failure and confirmed the findings of Wirtz and Mattila (2004) in online context. The author found that timely webcare (compared to delayed) in response to negative online reviews increases consumers´ forgiveness because they "perceive marketers as more empathetic to their problems, less guilty, and less responsible for the failure" (Ghosh, 2017 p.155).

In the current paper, we consider the timing of a webcare intervention in two ways. On the one hand, the timing of a webcare intervention relative to the start of a conversation indicates whether a webcare intervention occurs early or late in the conversation. On the other hand, the timing of a reactive webcare intervention relative to a specific consumer comment captures the speed (or quickness) by which the brand responds to consumer comments.

To test whether the timing of webcare interventions in consumer conversation on Facebook brand pages affects the conversation, we posit the following hypotheses:

H5. Early (versus late) webcare interventions in consumer conversations on Facebook brand pages result in a) a larger volume of subsequent consumer comments that b) contain more positive and less negative valence.

H6. Prompt (versus delayed) webcare interventions in consumer conversations on Facebook brand pages result in a) a larger volume of subsequent consumer comments that b) contain more positive and less negative valence.

Webcare can involve single or multiple brand interventions within the same consumer conversation. For example, a brand can respond to multiple consumers in a single reply or respond directly to each consumer individually as part of the same conversation. Such exchanges between a brands and consumers contribute to consumers' experiences with the brand. Brands conducting multiple successive webcare interventions within the same consumer conversation reinforce the exchange and create a cumulative effect of care experiences. These experiences may be stored as sensory or emotional impressions at the subconscious level contributing to strengthening the overall brand evaluation (Hofstede et al. 2007; Supphellen 2000). As such, multiple webcare interventions are therefore likely to have a stronger influence on subsequent consumer comments added to the conversation. Based on such reasoning, we propose the following hypothesis:

H7. Multiple (versus single) successive webcare interventions in consumer conversations on Facebook brand pages result in a) a larger volume of subsequent consumer comments that b) contain more positive and less negative valence.

In addition to the proposed direct effects, a number of interaction effects are likely. As no empirical evidence is available, we do not know how the timing, number and style of webcare interventions come together to influence consumer conversations. For example, if a brand manager decides to be proactive and take action early, is it better to craft a personal or impersonal webcare intervention? Or, if for some reason a brand manager's intervention is late, is it more effective to implement a single webcare intervention using a personal approach or best to execute multiple, impersonal interventions? The straightforward stance is that regardless of timing, whether prompt and early or delayed and late, it is most effective to put in place multiple, proactive personalized webcare interventions. Thus, we propose:

H8. Proactive (versus reactive), personal (versus impersonal) and multiple (versus single) successive webcare interventions in consumer conversations on Facebook brand pages combine to result in a) a larger volume of subsequent consumer comments that b) contain more positive and less negative valence.

Method

We use a large, longitudinal dataset collected from Facebook brand pages to assess the impact of webcare interventions on consumer conversations over time. Multivariate multilevel regression analyses were conducted to determine the extent to which activity type (reactive versus proactive), voice (personal versus impersonal), timing (early versus late and prompt versus delayed) and number (single versus multiple) of webcare interventions influence the volume and valence of consumer conversations.

Data collection

Data were collected from Facebook brand pages across 25 industry sectors using Facebook Graph API, a programmable interface allowing researchers to request and download content including brand posts, consumer comments and brand replies to comments. Selected brands were among those listed on the 2015 Inc.5000 annual brand list of the 5000 fastest-growing private companies in the U.S. published by Inc. Magazine. Brands with an official Facebook brand page were retained while those without one were excluded. The sample was further refined by considering only Facebook brand pages that: a) had at least one brand post during 2015, b) had at least 100 fans (page likes) and c) allowed data collection via the Facebook Graph API. The final sample comprised 2,740 Facebook brand pages and the gathered data covered consumer conversations occurring between 01/01/2015 and 31/12/2015, resulting in a considerably large dataset. The dataset included 107,784 consumer conversation threads (posts with at least one consumer comment), among which 24,557 (22.78%) conversations had webcare interventions. In total there was 1,706,656 individual consumer comments and 62,842 webcare interventions.

Measures

Proactive versus Reactive Webcare Interventions

We classified webcare interventions as either “reactive” for direct replies to explicit consumer comments or “proactive” otherwise. The reactivity and proactivity of single webcare interventions were either 0 or 1, while the reactivity (proactivity) of multiple webcare interventions was calculated as the proportion of reactive (proactive) ones. Overall, the majority of webcare interventions were reactive (n = 55,784, 88.77%).

Personal vs. Impersonal webcare interventions

In addition to reactive and proactive webcare interventions, brands often introduce a personal touch in their interventions by mentioning the name of a specific consumer. On Facebook, this practice is called “user tagging”. Figure 2 illustrates an example of personal webcare intervention using user tagging. An alternative form of personalization can also be measured as the use of second person pronouns in brand replies to consumer comments. LIWC is used to identify the presence of function words including second person pronouns (Pennebaker et al 2015) including “you, youd, you’d, youll, you’ll, your, youre, you’re yours, you’ve, you’ve, thee, thine, thou, thoust, thy, ya, yall, y’all, and ye” (Chung and Pennebaker 2007). The presence (vs. absence) of at least one of these words in the text of a webcare intervention signaled the presence (vs. absence) of second person pronoun, and thus the personalization of the webcare intervention. The presence of either or both user tagging and second person pronouns was used as an indicator of personalization, coding the independent variable WI Personalization (WIP) as 1, otherwise it is coded as 0. The personalization of single webcare interventions was either 0 or 1, while the personalization of multiple webcare interventions is calculated as the proportion of personalized ones. Most webcare interventions (n = 38,353, 61.03%) are personalized.

Figure 2. Personalized webcare intervention *using user tagging and second person pronouns.*

Timing of webcare intervention in the consumer conversation

We measured whether a webcare intervention occurred early or late in the across the timeline of the entire conversation using the time lag, in hours, between the webcare intervention and the first consumer comment in the conversation. Controlling for the timing of webcare interventions is important to study the effect of the other variables, given that early webcare interventions would naturally lead to more consumer comments after the intervention than before.

Promptness of reactive webcare interventions

We measured the promptness of reactive webcare interventions as the time lag between consumer comments and brand's response, in number of hours. This measure captures whether the interventions are prompt or delayed in response to consumers' comments. The promptness of multiple webcare interventions is calculated as the average promptness across those webcare interventions that are reactive in the same consumer conversation.

Single vs. Multiple Webcare Interventions

Multiple webcare interventions within the same consumer conversation are grouped into a single entry, tagged as "multiple" and aligned on the timing of the first webcare intervention, which helps highlight the cumulative effect of multiple webcare interventions on the volume and valence of consumer comments. The final sample size of webcare interventions (after grouping multiple webcare interventions together) was 22,973.

Volume and Valence of Consumer Conversations

The volume of a consumer conversation corresponds to the number of consumer comments it contains. The valence of consumer conversations was obtained by conducting a sentiment analysis of consumer comments using automated text analysis software LIWC2015 (Pennebaker et al 2015). LIWC supports a sentiment lexicon for positive and negative words and has been widely used in psychology and linguistics (Tausczik and Pennebaker 2010). The software calculates the relative frequency of words related to one polarity in a given text sample (e.g., the words "love", "nice", or "sweet" are counted as representatives of positive valence, while the words "hurt", "ugly", "nasty" are counted as representatives of negative valence). All comments within consumer conversations were classified as either positive or negative using the LIWC's Tone metric to differentiate between positive comments (Tone > 50) and negative comments (Tone < 50). The valence score of a consumer conversation is calculated as the proportion of positive comments and ranges between 0 and 1. Conversations with higher proportions of negative comments received scores closer to 0 whereas conversations with higher proportions of positive comments received scores closer to 1. Overall, the valence of consumer conversations averaged 0.61 (SD = 0.50), which shows that consumer conversations are mostly positive.

Volume and Valence of Consumer Conversations after Webcare Intervention

For each webcare intervention WI_x in a consumer conversation, we measured prior and subsequent volume, and valence of consumer comments subsequent to WI_x. To do that, we identified two sets of comments: $C_{WI_x}^{\ll}$ corresponding to the consumer comments prior to webcare intervention WI_x and $C_{WI_x}^{\gg}$ corresponding to the subsequent consumer comments. VO($C_{WI_x}^{\ll}$) and VA($C_{WI_x}^{\ll}$) note the volume and valence for the set of comments $C_{WI_x}^{\ll}$ prior to WI_x. VO($C_{WI_x}^{\gg}$) and VA($C_{WI_x}^{\gg}$) note the volume and valence for the set of comments $C_{WI_x}^{\gg}$ after WI_x.

Given that multiple webcare interventions occurring within the same conversation are being grouped and that the timing of the first intervention is retained, the sets of prior comments $C_{WI_x}^{\ll}$ and subsequent comments $C_{WI_x}^{\gg}$ of a "multiple" webcare intervention WI_x are those before and after the first webcare intervention.

In order to estimate the shift in volume after a webcare intervention compared to the volume before the webcare intervention, relative values are considered instead of absolute ones. For instance, the shift in volume of consumer comments, noted $ShiftVO(WI_x)$ is calculated as:

$$ShiftVO(WI_x) = \frac{VO\left(C_{WI_x}^{\gg}\right) - VO\left(C_{WI_x}^{\ll}\right)}{VO\left(C_{WI_x}^{\ll}\right) + VO(C_{WI_x}^{\gg})}$$

$ShiftVO(WI_x)$ ranges from -1 to +1. Values of $ShiftVO(WI_x)$ closer to -1 indicate that the volume of the conversation after a webcare intervention is a lot smaller than the volume before the webcare intervention whereas values closer to +1 indicate the volume is larger after webcare compared to before the intervention. Similarly, the shift in valence of consumer comments, noted $ShiftVA(WI_x)$, considered to estimate the change in valence after a webcare intervention compared to the valence of the consumer comments prior to the webcare intervention, is calculated as:

$$ShiftVA(WI_x) = \frac{VA\left(C_{WI_x}^{\gg}\right) - VA\left(C_{WI_x}^{\ll}\right)}{VA\left(C_{WI_x}^{\ll}\right) + VA\left(C_{WI_x}^{\gg}\right)}$$

The values of $ShiftVA$ also lie between -1 and +1. The closer to +1, the greater the shift in one direction towards more positive comments, and the closer to -1 the greater the shift in the opposite direction towards more negative comments. For example, if all consumer comments prior to a webcare intervention WI_x had a negative valence, and all subsequent consumer comments had a positive valence, $ShiftVA(WI_x) = +1$.

Control: Industry Sector

To control for industry sector, the 25 sectors were aggregated into five categories adapted from the UN high-level aggregation of the International Standard Industrial Classification (ISIC) of all economic activities (ISIC revision 4 2008). The Industry categories were coded as five dummy variables Ind1 to Ind5, respectively "Business products and services" (n = 694, 25.3%), "Information and Communication Technologies" (n = 662, 24.2%), "Consumer products and services" (n = 603, 22.0%), "Manufacturing, construction and industrial activities" (n = 394, 14.4%), and "Public services" (n = 387, 14.1%).

Results

Preliminary analyses on the complete dataset show the volume of consumer comments per conversation ranges from 1 to 31,973, averaging 15.83 (sd = 137.73) with a positively skewed distribution (skewness = 132.57, kurtosis = 27846.68). Consumer conversations with webcare interventions contain a higher volume of comments (mean = 32.74, sd = 1.11) and slightly lower valence (mean = 0.49, sd = 0.002) compared to the volume (mean = 11.25, sd = 0.44) and valence (mean = 0.50, sd = 0.001) for conversations without webcare interventions. Separate ANCOVA models with industry included as a covariate show these differences for both volume ($F(1, 107{,}778) = 5704.13$, $p < .001$) and valence ($F(1, 107{,}778) = 7.75$, $p < .005$) to be statistically significant. These results indicate that brands conduct webcare interventions mostly in consumer conversations with high volumes of comments and more negative valence, supporting hypothesis H1.

Descriptive statistics of the volume and valence of consumer conversations vary among industry sectors. Consumer products and services was found to have the highest volume of consumer comments (mean = 23.06, se = 0.76), followed by public services (mean = 12.96, se = 0.76), and business products and services having the least consumer comments per conversation (mean = 3.19, se = 0.11). In regards to the valence of consumer conversations, business products and services have the highest valence (mean = 0.57, se = 0.004), followed by information and communication technologies (mean = 0.52, se = 0.004), with public services having the lowest valence (mean = 0.47, se = 0.003).

Effect of webcare interventions on consumer conversations

To examine the causal effect of webcare interventions on the volume and valence of consumer comments, we focus on the subset of 24,557consumer conversations that contain 62,842 webcare interventions. Table 1 summarizes the descriptive statistics. Paired t-tests comparing the mean volume and valence before and after webcare interventions indicate significant differences for volume ($t = -7.40$, $p < 0.001$) and valence ($t = 17.63$, $p < 0.001$), in support of hypothesis H2. While the volume of consumer comments is, on average, larger after a brand intervention, their valence is found to be less positive and more negative after the intervention. However, these results should be taken with a grain of salt as they do not differentiate between reactive or proactive, single or multiple, personal or impersonal, early or late, prompt or delayed webcare interventions, which is the subject of the subsequent analysis.

Using two multivariate multi-level hierarchical regression analyses, we examine the role of webcare intervention characteristics as moderators of shifts in volume ($ShiftVO$) and valence

($ShiftVA$) of consumer comments. For each of these outcome variables, we regress the characteristics of webcare intervention, namely reactive (vs proactive), early (vs late), personal (vs impersonal) and multiple (vs single) BIs in the first multivariate multi-level hierarchical regression. A second multivariate multi-level hierarchical regression is conducted for reactive webcare interventions only to include the promptness (prompt vs. delayed) of the intervention as predictor. In addition, aiming to examine the nature of the associations between these explanatory variables, the two-way and three-way combinations of the characteristics of webcare interventions are tested as joint effects and plotting of the identified interactions using the procedures suggested by Aiken and West (1991) are included. Normality of the distribution of the variables and linearity of the relationship between dependent and independent variables have been examined to ensure the requirements of multi-level hierarchical regression analysis are met and a linear relationship exists. Furthermore, the assumption of multicollinearity was tested using the variance inflation factors (VIF) for the set of independent variables and for each predicted outcome. VIF of 10 (equivalent to a tolerance level of 0.10) has been used as a rule of thumb to indicate excessive or serious multicollinearity (Menard 1995; Neter et al 1989; Marquardt 1970; Mason et al 2003). VIF levels for all independent variables and for the all the hierarchical models are well under 10, showing acceptable multicollinearity. In addition, the condition index for all predictors are well under 30 which further excludes collinearity.

Table 1. Descriptive statistics of webcare interventions

Webcare interventions	**# Observations**	**%**
All	*62,842*	*100%*
Single	*14,031*	*22.33%*
Multiple	*48,811*	*77.67%*
Reactive	*55,784*	*88.77%*
Proactive	*7,058*	*11.23%*
Personal	*47,051*	*74.87%*
Impersonal	*15,791*	*25.13%*

Table 2. Comparison of means of volume and valence before and after webcare intervention

	Min	Mean	Max	SD
Volume before webcare intervention	*0*	*19.42*	*5,571*	*110.80*
Volume after webcare intervention	*0*	*13.25*	*6,954*	*99.48*
Valence before webcare intervention	*0*	*0.47*	*1*	*0.39*
Valence after webcare intervention	*0*	*0.51*	*1*	*0.35*

Results

Table 3 provides the results of the first multi-level hierarchical regression analysis explaining the shift in volume of consumer comments ($ShiftVO$) and the shift in valence of consumer comments ($ShiftVA$). As shown in Table 3, we started with a baseline model that includes only the random effects at both the industry and brand levels for each of $ShiftVO$ (Model VO1.0) and $ShiftVA$ (Model VA1.0). Models VO1.1 and VA1.1 add the main effect of the explanatory variables including whether webcare interventions are reactive (vs. proactive), personal (vs. impersonal), multiple (vs. single), as well as the timing of webcare interventions. Models VO1.2 and VA1.2 include the two-way interactions between the explanatory variables proposed in the research hypotheses. Similarly, models VO1.3 and VA1.3 include the three-way interactions between the explanatory variables. Finally, models VO1.4 and VA1.4 include the four-way interactions between the explanatory variables. Incremental marginal R^2 tests indicate that adding the explanatory variables and the interaction terms (up to the three-way interactions) improve the models' ability to explain the shift in volume and valence of consumer comments following a webcare intervention. All models' incremental R^2 tests are significant and indicate that Models VO1.3 and VA1.3 have the best fit to the data respectively for $ShiftVO$ and $ShiftVA$.

The results indicate that proactive webcare interventions have a positive association with both the shift in volume ($\beta = 0.35$, $p<0.001$) and valence of consumer comments ($\beta = 0.29$, $p<0.001$). In other words, proactive webcare interventions are found to be associated with higher volume and higher valence of consumer comments after the intervention than before, which supports hypothesis H3. However, contrary to our predictions, the results demonstrate that personal webcare interventions are negatively associated with the shift in valence ($\beta = -0.03$, $p<0.001$) and have no significant association with the shift in volume, rejecting hypothesis H4. The results also show that early webcare interventions are positively related to the shift in volume and valence of consumer comments, given that the timing of webcare interventions, measured as the number of hours since the start of the conversation, is negatively associated with the shift in volume ($\beta = -0.35$, $p<0.001$) and shift in valence ($\beta = -0.17$, $p<0.001$). This finding confirms our prediction that webcare interventions occurring early in the conversation generate more favorable consumer reactions and supports hypothesis H5. Furthermore, the results show that, compared to single webcare interventions, the effect of multiple webcare interventions is positive on the shift in volume of consumer comments ($\beta = 0.25$, $p<0.001$) and on the shift in valence of consumer comments ($\beta = 0.16$, $p<0.01$). This finding provides evidence of a positive cumulative effect of multiple webcare interventions and supports hypothesis H7.

Further to the direct effects of the explanatory variables, their interaction effects are also statistically significant for various two-way and three-way interactions as reported in Table 3. We visually depict two-way interactions in figure 2, following Aiken and West (1991). Specifically, we used the predicted values at one standard deviation above and below the mean of each explanatory variable. Note that interactions were plotted at the minimum (maximum) value of a variable if one standard deviation below (above) the mean was smaller (larger) than the minimum (maximum) value of the variable.

Table 3. Results of the first multi-level hierarchical regression analysis of $ShiftVO$ and $ShiftVA$

	Multi-level hierarchical models of shift in volume of consumer comments $ShiftVO$					Multi-level hierarchical models of shift in valence of consumer comments $ShiftVA$				
	Model VO1.0 Random Effects	**Model VO1.1** Main effects	**Model VO1.2** Main effects & 2 way interactions	**Model VO1.3** Main effects & 3 way interactions	**Model VO1.4** Main effects & 4 way interactions	**Model VA1.0** Random Effects	**Model VA1.1** Main effects	**Model VA1.2** Main effects & 2 way interactions	**Model VA1.3** Main effects & 3 way interactions	**Model VA1.4** Main effects & 4 way interactions
	β | SE	β | SE	β | SE	β | SE	β | SE	β | SE	β | SE	β | SE	β | SE	β | SE
Intercept	-0.37 | 0.02	-0.06* | 0.02	0 | 0.03	-0.05 | 0.03	-0.06 | 0.03	-0.17 | 0.02	0.05* | 0.02	0.33*** | 0.03	0.43*** | 0.04	0.44*** | 0.04
Proactive (PR)		0.07*** | 0.01	0.23*** | 0.03	0.35*** | 0.04	0.35*** | 0.04		0.06*** | 0.01	0.20*** | 0.03	0.29*** | 0.05	0.29*** | 0.05
Personal (PE)		-0.02*** | 0.01	-0.05*** | 0.02	-0.01 | 0.03	-0.01 | 0.03		-0.02** | 0.01	-0.06*** | 0.03	-0.03*** | 0.05	-0.02*** | 0.05
Multiple (M)		0.42*** | 0.01	0.27*** | 0.03	0.25*** | 0.05	0.27*** | 0.05		0.25*** | 0.01	0.16*** | 0.04	0.16** | 0.08	0.17 | 0.13
Timing (T) ▪		-0.32*** | 0.00	-0.39*** | 0.01	-0.35*** | 0.01	-0.35*** | 0.01		-0.15*** | 0.00	-0.20*** | 0.01	-0.17*** | 0.01	-0.17*** | 0.01
Interaction effects										
PR × T			-0.09*** | 0.01	-0.25*** | 0.01	-0.26*** | 0.01			-0.11*** | 0.01	-0.22*** | 0.02	-0.23*** | 0.02
PE × T			0.09*** | 0.01	0.03 | 0.01	0.03 | 0.01			0.09*** | 0.01	0.05*** | 0.02	0.04*** | 0.02
M × T			0.19*** | 0.01	0.19*** | 0.01	0.17*** | 0.02			0.09*** | 0.01	0.09*** | 0.02	0.07** | 0.05
PR × PE			-0.11*** | 0.02	-0.23*** | 0.05	-0.24*** | 0.05			-0.08*** | 0.03	-0.17*** | 0.05	-0.18*** | 0.06
PR × M			0.01* | 0.03	0.00 | 0.07	-0.04 | 0.13			0.03*** | 0.03	0.00 | 0.08	-0.03 | 0.15
PE × M			-0.02 | 0.02	0.04 | 0.06	0.02 | 0.06			0.00 | 0.03	0.03 | 0.09	0.01 | 0.17
PR × PE × T				0.18*** | 0.02	0.19*** | 0.02				0.12*** | 0.02	0.14*** | 0.02
PR × M × T				0.07*** | 0.02	0.13** | 0.05				0.04* | 0.02	0.09. | 0.05
PR × PE × M				-0.06*** | 0.07	0.00 | 0.17				-0.01 | 0.08	0.03 | 0.19
T × PE × M				-0.04 | 0.02	-0.01 | 0.02				-0.03 | 0.02	0.00 | 0.05
PR × T × PE × M					-0.07 | 0.05					-0.05 | 0.06
Random effects	σ2 | SD	σ2 | SD	σ2 | SD	σ2 | SD	σ2 | SD	σ2 | SD	σ2 | SD	σ2 | SD	σ2 | SD	σ2 | SD
Between-brands	0.065 | 0.254	0.045 | 0.213	0.041 | 0.203	0.040 | 0.200	0.040 | 0.200	0.028 | 0.167	0.021 | 0.145	0.019 | 0.139	0.019 | 0.138	0.019 | 0.137
Between-industries	0.001 | 0.038	0.001 | 0.039	0.002 | 0.040	0.002 | 0.042	0.002 | 0.042	0.001 | 0.034	0.001 | 0.032	0.001 | 0.033	0.001 | 0.034	0.001 | 0.034
Marginal R^2	0.000	0.247	0.260	0.263	0.263	0.000	0.079	0.086	0.087	0.087
Conditional R^2	0.145	0.350	0.355	0.355	0.355	0.066	0.129	0.133	0.133	0.133
Incremental R^2		0.247***	0.013***	0.003***	0.000		0.079***	0.007***	0.001***	0.000
Model retained?	–	✅	✅	✅	⛔	–	✅	✅	✅	⛔

β=standardized parameter estimate; SE: Standard Error; σ^2=variance component; SD=Standard Deviation; Significance Codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
▪ Timing is a continuous variable (low=early, high=late)

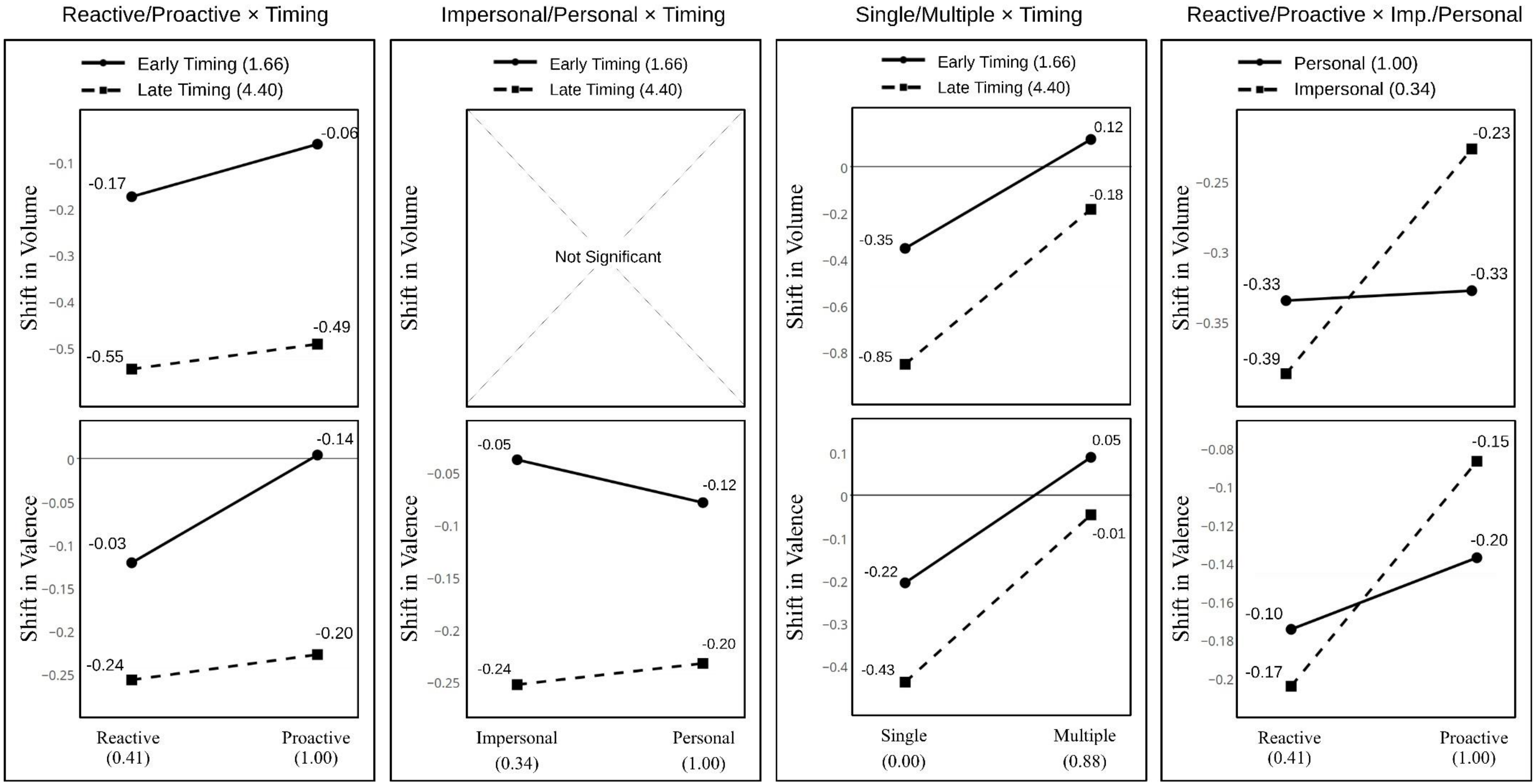


Figure 3. Two-way interaction effects of Reactive/Proactive, Impersonal/Personal, Single/Multiple and Early/Late webcare interventions

The interaction between reactive/proactive and the timing of webcare interventions is statistically significant for both the volume ($\beta = -0.25$, $p<0.001$) and valence of consumer comments ($\beta = -0.22$, $p<0.001$), as shown in Table 3. This interaction is visually depicted in *Figure 3* (Reactive/Proactive × Timing), indicating that the positive association between proactive webcare interventions and both the shifts in volume and valence of consumer comments is stronger when brands intervene early in the conversation than when they intervene late. Another interesting finding worth noting is that, when webcare interventions occur late in the conversation, reactive interventions are associated with higher shifts in volume and valence of consumer comments than proactive ones. These findings are confirmed by the simple slopes showing negative and statistically significant coefficients of proactive webcare interventions for both early interventions ($\beta = 0.34$, $p<0.001$ for volume and $\beta = 0.26$, $p<0.001$ for valence) and late interventions ($\beta = 0.08$, $p<0.001$ for volume and $\beta = 0.06$, $p<0.001$ for valence). Importantly, the slopes for early webcare interventions are steeper than those of late webcare interventions in the conversation.

The interaction between reactive/proactive and personal/impersonal webcare interventions is also statistically significant for both the volume ($\beta = -0.23$, $p<0.001$) and valence of consumer comments ($\beta = -0.17$, $p<0.001$), as shown in Table 3. This interaction is visually depicted in *Figure 3* (Reactive/Proactive × Imp./Personal), indicating that the positive association between proactive webcare interventions and the shifts in volume and valence of consumer comments is weaker for personal interventions, compared to impersonal ones. This finding suggests that brands should favor impersonal proactive over personal proactive, and personal reactive over impersonal reactive webcare interventions. This is also validated by the simple slopes showing negative and statistically significant coefficients of reactive webcare interventions for both personal interventions ($\beta = -0.18$, $p<0.001$ for volume and $\beta = -0.17$, $p<0.001$ for valence) and impersonal interventions ($\beta = -0.40$, $p<0.001$ for volume and $\beta = -0.32$, $p<0.001$ for valence), indicating steeper slopes for impersonal reactive webcare interventions than those of personal reactive webcare interventions.

The interactions between personal/impersonal and timing of webcare interventions is statistically significant for the valence of consumer comments ($\beta = 0.05$, $p<0.001$), as shown in Table 3. These interactions are visually depicted in *Figure 3* (Impersonal/Personal × Timing) indicating that, regardless of whether webcare interventions are personal or impersonal, late interventions have a more negative association with the shift in valence of consumer comments than early interventions. In particular, early impersonal webcare interventions have a less negative association with the shift in valence of consumer comments than early personal interventions, and late personal webcare interventions have a less negative association with the shift in valence of consumer comments than late impersonal interventions. This indicates that a personal webcare intervention is more effective when the webcare intervention occurs late in the conversation. These results are also confirmed by simple slope tests showing a steeper slope for personal webcare interventions ($\beta = -0.34$, $p<0.001$), than impersonal webcare interventions ($\beta = -0.28$, $p<0.001$) on the valence of consumer comments.

Finally, the interactions between single/multiple and the timing of webcare interventions is statistically significant for both the volume (respectively $\beta = 0.19$, $p<0.001$ and $\beta = 0.38$, $p<0.001$) and valence of consumer comments (respectively $\beta = 0.09$, $p<0.05$ and $\beta = 0.15$, $p<0.001$), as shown in Table 3. These interactions are visually depicted in *Figure 3* (Single/Multiple × Timing) indicating that early and multiple interventions have a more positive association with the shift in volume and valence of consumer comments than single and late interventions. These results are confirmed by simple slope tests showing a steeper positive slope on the volume of consumer comments for multiple webcare interventions ($\beta = 0.89$, $p<0.001$) than single webcare interventions ($\beta = 0.49$, $p<0.001$), and a steeper slope on the valence of consumer comments for multiple webcare interventions ($\beta = 0.53$, $p<0.001$), than single webcare interventions ($\beta = 0.38$, $p<0.001$).

Three-way interactions were also found to be statistically significant and reveal several interesting findings. While late webcare interventions, even when proactive, were found to be negatively associated with the shift in volume and valence of consumer comments, late proactive personal interventions are, instead, positively associated with the shift in volume ($\beta = 0.18$, $p<0.001$) and valence ($\beta = 0.12$, $p<0.001$) of consumer comments. Although the direct effect of timing of webcare interventions is negative and stronger than the three-way interaction effect (when comparing the absolute values of the β coefficients), this finding indicates the overall positive contribution of personal webcare interventions. Similarly but to a lesser extent, late proactive multiple interventions are also positively associated with the shift in volume ($\beta = 0.07$, $p<0.001$) and valence ($\beta = 0.04$, $p<0.05$) of consumer comments, indicating that when webcare interventions are late, having multiple interventions can counter the negative effect of timing. Nevertheless, this overall positive effect is not scalable when multiple proactive and personal webcare interventions are conducted as they are negatively associated with the shift in volume of consumer comments and have no significant association with the shift in valence of consumer comments. This later result rejects hypothesis H8 which stated that it is most effective to put in place multiple, proactive personalized webcare interventions.

While the timing of webcare intervention was considered in the above analysis, reactive webcare interventions can also be prompt or delayed relative to the consumer comments they respond to. In order to evaluate the effect of the time lag between a brand intervention and the comment it replies to, a second multi-level hierarchical regression was conducted for reactive webcare interventions only and included the promptness (prompt vs. delayed) of the intervention as predictor among the other predictors.

Similarly to the first regression, we started with a baseline model that includes only the random effects at both the industry and brand levels for each of ShiftVO (Model VO2.0) and ShiftVA (Model VA2.0). Models VO2.1 and VA2.1 add the main effect of the explanatory variables including whether webcare interventions are personal (vs. impersonal), multiple (vs. single), as well as the timing and promptness of webcare interventions. Models VO2.2 and

VA2.2 include the two-way interactions between the explanatory variables proposed in the research hypotheses. Similarly, models VO2.3 and VA2.3 include the three-way interactions between the explanatory variables. Finally, models VO2.4 and VA2.4 include the four-way interactions between the explanatory variables. Incremental marginal R2 tests indicate that adding the explanatory variables and the interaction terms (up to the three-way interactions for ShiftVO and up to the two-way interaction for ShiftVA) improve the models' ability to explain the shift in volume and valence of consumer comments following a webcare intervention. All models' incremental R2 tests are significant and indicate that Models VO2.3 and VA2.2 have the best fit to the data respectively for ShiftVO and ShiftVA.

The results reported in Table 4 confirm some of the same findings as the first multi-level multi-variate regression analysis including the positive effect of multiple webcare interventions and the negative effect of late webcare interventions on both volume and valence of consumer comments. In addition, delayed reactive webcare interventions were found to be associated with lower shifts in both volume ($\beta = -0.37$, $p<0.001$) and valence ($\beta = -0.11$, $p<0.001$) of consumer comments, indicating that prompt replies to consumer comments, i.e. low time lag between reactive webcare interventions and the comments they respond to, yield better outcome for both volume and valence of consumer comments, thus supporting hypothesis H6.

Table 4. Results of the second multi-level hierarchical regression analysis of $ShiftVO$ and $ShiftVA$ focusing on reactive webcare interventions

<table>
<tr><th></th><th colspan="5">Multi-level hierarchical models of shift in volume of consumer comments $ShiftVO$</th><th colspan="5">Multi-level hierarchical models of shift in valence of consumer comments $ShiftVA$</th></tr>
<tr><th></th><th>Model VO2.0
Random Effects</th><th>Model VO2.1
Main effects</th><th>Model VO2.2
Main effects & 2 way interactions</th><th>Model VO2.3
Main effects & 3 way interactions</th><th>Model VO2.4
Main effects & 4 way interactions</th><th>Model VA2.0
Random Effects</th><th>Model VA2.1
Main effects</th><th>Model VA2.2
Main effects & 2 way interactions</th><th>Model VA2.3
Main effects & 3 way interactions</th><th>Model VA2.4
Main effects & 4 way interactions</th></tr>
<tr><th></th><th>β | SE</th><th>β | SE</th><th>β | SE</th><th>β | SE</th><th>β | SE</th><th>β | SE</th><th>β | SE</th><th>β | SE</th><th>β | SE</th><th>β | SE</th></tr>
<tr><td>Intercept</td><td>-0.45 | 0.03</td><td>-0.2** | 0.03</td><td>-0.02 | 0.04</td><td>0.00 | 0.04</td><td>| 0.04</td><td>-0.21 | 0.02</td><td>-0.14*** | 0.02</td><td>-0.05 | 0.03</td><td>-0.05 | 0.04</td><td>-0.04 | 0.04</td></tr>
<tr><td>Personal (PE)</td><td></td><td>0.02** | 0.01</td><td>0.01 | 0.02</td><td>0 | 0.03</td><td>0 | 0.03</td><td></td><td>0.01 | 0.01</td><td>-0.02 | 0.03</td><td>-0.02 | 0.04</td><td>-0.02 | 0.04</td></tr>
<tr><td>Multiple (M)</td><td></td><td>0.44*** | 0.01</td><td>0.27*** | 0.03</td><td>0.22*** | 0.05</td><td>0.21*** | 0.07</td><td></td><td>0.24*** | 0.01</td><td>0.16*** | 0.03</td><td>0.14** | 0.06</td><td>0.13* | 0.08</td></tr>
<tr><td>Timing (T) ▪</td><td></td><td>-0.16*** | 0</td><td>-0.32*** | 0.01</td><td>-0.35*** | 0.01</td><td>-0.35*** | 0.01</td><td></td><td>-0.07*** | 0.01</td><td>-0.15*** | 0.01</td><td>-0.16*** | 0.01</td><td>-0.16*** | 0.01</td></tr>
<tr><td>Time Lag (L) ▲</td><td></td><td>-0.2*** | 0</td><td>-0.35*** | 0.01</td><td>-0.37*** | 0.02</td><td>-0.37*** | 0.02</td><td></td><td>-0.08*** | 0</td><td>-0.11*** | 0.01</td><td>-0.09 | 0.02</td><td>-0.09. | 0.03</td></tr>
<tr><td>Interaction effects</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>T × L</td><td></td><td></td><td>0.3*** | 0</td><td>0.36*** | 0</td><td>0.36*** | 0.01</td><td></td><td></td><td>0.08** | 0</td><td>0.07 | 0.01</td><td>0.08 | 0.01</td></tr>
<tr><td>T × PE</td><td></td><td></td><td>0.01 | 0.01</td><td>0.04 | 0.01</td><td>0.04 | 0.01</td><td></td><td></td><td>0.04 | 0.01</td><td>0.06 | 0.02</td><td>0.06 | 0.02</td></tr>
<tr><td>T × M</td><td></td><td></td><td>0.39*** | 0.01</td><td>0.55*** | 0.02</td><td>0.56*** | 0.03</td><td></td><td></td><td>0.14*** | 0.01</td><td>0.25** | 0.03</td><td>0.27** | 0.03</td></tr>
<tr><td>L × PE</td><td></td><td></td><td>-0.02 | 0.01</td><td>-0.02 | 0.02</td><td>-0.02 | 0.02</td><td></td><td></td><td>-0.01 | 0.01</td><td>-0.05 | 0.03</td><td>-0.04 | 0.03</td></tr>
<tr><td>L × M</td><td></td><td></td><td>-0.26*** | 0.01</td><td>-0.29*** | 0.03</td><td>-0.28** | 0.04</td><td></td><td></td><td>-0.07*** | 0.01</td><td>-0.16* | 0.03</td><td>-0.13 | 0.05</td></tr>
<tr><td>PE × M</td><td></td><td></td><td>0.04* | 0.02</td><td>0.05 | 0.06</td><td>0.06 | 0.08</td><td></td><td></td><td>0.02 | 0.03</td><td>0.03 | 0.07</td><td>0.04 | 0.1</td></tr>
<tr><td>T × L × PE</td><td></td><td></td><td></td><td>-0.02 | 0.01</td><td>-0.03 | 0.01</td><td></td><td></td><td></td><td>0.02 | 0.01</td><td>0.01 | 0.01</td></tr>
<tr><td>T × L × M</td><td></td><td></td><td></td><td>-0.09* | 0</td><td>-0.11 | 0.01</td><td></td><td></td><td></td><td>-0.01 | 0</td><td>-0.05 | 0.01</td></tr>
<tr><td>T × PE × M</td><td></td><td></td><td></td><td>-0.13. | 0.03</td><td>-0.14. | 0.03</td><td></td><td></td><td></td><td>-0.11 | 0.03</td><td>-0.13 | 0.04</td></tr>
<tr><td>L × PE × M</td><td></td><td></td><td></td><td>0.12* | 0.03</td><td>0.11 | 0.05</td><td></td><td></td><td></td><td>0.11* | 0.03</td><td>0.08 | 0.06</td></tr>
<tr><td>T × L × PE × M</td><td></td><td></td><td></td><td></td><td>0.02 | 0.01</td><td></td><td></td><td></td><td></td><td>0.04 | 0.01</td></tr>
<tr><td>Random effects</td><td>σ2 | SD</td><td>σ2 | SD</td><td>σ2 | SD</td><td>σ2 | SD</td><td>σ2 | SD</td><td>σ2 | SD</td><td>σ2 | SD</td><td>σ2 | SD</td><td>σ2 | SD</td><td>σ2 | SD</td></tr>
<tr><td>Between-brands</td><td>0.053 | 0.231</td><td>0.031 | 0.175</td><td>0.028 | 0.169</td><td>0.029 | 0.169</td><td>0.029 | 0.169</td><td>0.025 | 0.159</td><td>0.019 | 0.137</td><td>0.018 | 0.136</td><td>0.018 | 0.136</td><td>0.018 | 0.136</td></tr>
<tr><td>Between-industries</td><td>0.005 | 0.07</td><td>0.004 | 0.066</td><td>0.004 | 0.066</td><td>0.004 | 0.065</td><td>0.004 | 0.065</td><td>0.002 | 0.041</td><td>0.001 | 0.033</td><td>0.001 | 0.033</td><td>0.001 | 0.032</td><td>0.001 | 0.032</td></tr>
<tr><td>Marginal R^2</td><td>0.000</td><td>0.275</td><td>0.296</td><td>0.296</td><td>0.296</td><td>0.000</td><td>0.070</td><td>0.073</td><td>0.073</td><td>0.073</td></tr>
<tr><td>Conditional R^2</td><td>0.142</td><td>0.362</td><td>0.377</td><td>0.377</td><td>0.377</td><td>0.065</td><td>0.118</td><td>0.120</td><td>0.120</td><td>0.120</td></tr>
<tr><td>Incremental R^2</td><td></td><td>0.205***</td><td>0.005***</td><td>0.000*</td><td>0.000</td><td></td><td>0.070***</td><td>0.003***</td><td>0.000</td><td>0.000</td></tr>
<tr><td>Model retained?</td><td>–</td><td>✅</td><td>✅</td><td>✅</td><td>⛔</td><td>–</td><td>✅</td><td>✅</td><td>⛔</td><td>⛔</td></tr>
</table>

β=standardized parameter estimate; SE: Standard Error; σ^2=variance component; SD=Standard Deviation; Significance Codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

▪ Timing is a continuous variable (low=early, high=late); ▲ Time Lag indicates the promptness of webcare interventions (low=prompt, high=delayed)

Interaction effects were also found to be significant. For instance, the results confirm the same findings as the first regression analysis regarding the positive interaction between single/multiple and the timing of webcare interventions. Surprisingly, the interaction between the promptness and timing of webcare interventions was found to be positively associated with the shift of both volume ($\beta = 0.36$, $p<0.001$) and valence ($\beta = 0.08$, $p<0.01$) of consumer comments, indicating that despite being late in the conversation, delayed reactive webcare interventions have a positive effect on consumer subsequent comments. A possible explanation could be that, as the conversation builds up over time, the longer brand managers delay their reactive webcare interventions, the more consumer-to-consumer interactions take place leading to more positive outcomes. Furthermore, the results in Table 4 indicate that prompt webcare interventions are better than delayed ones for both volume and valence of consumer comments, and that the difference is greater in the case of multiple webcare interventions. In other words, repeatedly delayed replies to consumer comments has a negative effect on both volume ($\beta = -0.29$, $p<0.001$) and valence ($\beta = -0.07$, $p<0.001$) of consumer comments.

Discussion

The purpose of this study was to first examine the causal relationship between webcare intervention and the shift in volume and valence of consumer conversations. Initial findings provide evidence of a statistically significant effect of webcare interventions on the volume and valence of subsequent consumer comments. The results also provide insights into how webcare intervention characteristics play a role in moderating its effect on the volume and valence of consumer comments. Key highlights of this study suggest that proactive, impersonal, and frequent (multiple) webcare interventions occurring early in the conversation have significant positive effects on both the volume and valence of consumer comments. Furthermore, the findings suggest that when brand managers conduct reactive webcare interventions, their promptness in replying to consumer comments has a positive effect.

The results of this study provide new insights extending prior research on the effect of personal webcare interventions on consumer conversations. Contrary to previous research emphasising that brand humanization in webcare is effective at mitigating negative WOM and enhancing favourable consumer reactions (Lee and Song 2010; van Noort and Willemsen 2012), this research suggests that personal webcare interventions have in fact the opposite effect in the context of online consumer conversation on social networking platforms such as Facebook. Furthermore, contrary to the findings of Schamari and Schaefers (2015) arguing that brand humanization in webcare affect only consumer generated platforms (in driving positive consumer engagement) and not in brand generated platforms, this study provides further evidence that the anthropomorphization in (personal) webcare intervention affects both consumer generated platform and brand generated platform as we consider that Facebook brand pages entails both B2C and C2C interactions.

This study further demonstrates the significant interaction effects among the explanatory variables. Interestingly, the results demonstrate that impersonal proactive webcare interventions have a greater effect than personal proactive ones. Likewise, the findings suggest that impersonal proactive webcare interventions have a much greater effect than impersonal reactive webcare interventions. Although these findings might seem counter-intuitive, a possible rationale may be primarily related to the one-to-many nature of brand communication on Facebook brand pages instead of the one-to-one communication pattern of traditional brand-consumer correspondence. Indeed, a brand reply to a specific consumer comment on Facebook is visible to all consumers. Therefore, personal (impersonal) brand replies would have more (less) effect on the one consumer replied to, and less (more) effect on the rest of all consumers.

General Discussion

The results of this study, supported by large field data from consumer conversations on Facebook brand pages including diverse webcare strategies (reactive, proactive, single, multiple, personal, impersonal, early, late, prompt or delayed), provide real world evidence that webcare interventions affect consumer conversations in terms of volume and valence of consumer comments. Specifically, the initial analysis conducted in this study empirically demonstrates the causal effects of webcare interventions on the shift in volume and valence of consumer comments after webcare intervention. In particular, the findings provide evidence of a positive cumulative effect of multiple webcare interventions on both the shift in volume and valence of consumer comments. Results also show a negative effect of reactive webcare interventions compared to proactive ones, on both the shift in volume and valence. Such negative effect on the volume of consumer comments is attenuated by the promptness of reactive webcare interventions. Furthermore, personal webcare interventions as well as late interventions were found to have a negative effect on both the shift in volume and valence.

Managerial implications

The current research has several managerial implications. Facebook represents the largest and most widely used platform for online conversations connecting over 2 billion monthly active users as of June 2017. This remarkable growth has led over 60 million businesses to create Facebook brand pages[1] for engaging with their consumers. According to Global Web Index (2015), 44% of Facebook users follow their favourite brands on Facebook brand pages. This new scale of brand-consumer and consumer-consumer interactions has led to unprecedented increase in consumer generated content reaching a total of 2.5 billion comments every month on Facebook brand pages. In this era of empowered consumers, marketers encounter new challenges into how to effectively manage consumer conversations on Facebook brand pages. The current research helps to address these challenges by examining whether webcare intervention in online consumer conversations matters and investigate its effects on online consumer conversations.

Our findings suggest that marketing practitioners should carefully consider several key

[1] https://www.facebook.com/business/news/new-tools-for-managing-communication-on-your-page

elements in the design and implementation of their webcare strategies in online consumer conversations. As the cumulative effect of multiple webcare interventions has been found to be positive and significant, brand managers should focus their efforts on continuous monitoring of consumer conversations and frequent webcare intervention throughout the conversation. A particular attention should be paid to early webcare intervention rather than late, such that marketers should prioritize interventions during the early stage of a conversation, which is likely to engender stronger positive effect. Nevertheless, when practitioners have to intervene in a reactive way (replying to individual comments), they should not do it too promptly when the conversation is already well established among consumers (i.e. late in the conversation). Instead, giving time to the consumers to interact before webcare interventions occur is shown to have a positive effect. Nonetheless, our findings indicate that proactive webcare interventions have a positive effect on consumer conversations compared to reactive ones. Thereby, marketers should exert a greater care to intervene proactively, yet continue to intervene reactively when needed.

Limitations and further research

Despite these contributions, this paper entails some limitations that could be the focus of future research. First, our results are based on Facebook conversations, therefore, caution is warranted in generalizing the findings to other online social media platforms such as Twitter, Google+, LinkedIn or Instagram. Future studies may wish to examine the dynamics of webcare intervention effects in other social networking platforms, widening the scope of this research. Second, with the staggering uptake of mobile social networking, more than 1.74 billion monthly active users connect to Facebook on their mobile devices. A new shift in the paradigm of consumer-brand interactions is announced, with constant connection and instant messaging being the key new characteristics of such shift. In particular, with the recent introduction of chat bots by Facebook, the inherently personal nature of consumer real-time interaction on Facebook Messenger is becoming a brand platform where brands can interact in real time with consumers instead of intervening sporadically in consumer conversations. Mobile social networking would be an interesting avenue for future research on the dynamics of real-time webcare interventions in consumer conversations but also the advent of large scale one-to-one brand-consumer conversations. Finally, the findings of this research suggest that brand managers should intervene proactively and multiple times within the same consumer conversation. It would be of interest to further investigate the effect of the time lag between webcare interventions on consumer engagement to identify an optimal frequency of proactive webcare interventions.

References

Aiken, Leona S., Stephen G. West, and Raymond R. Reno. (1991), *Multiple regression: Testing and interpreting interactions*. Sage.

Belch, George E. (1982), "The effects of television commercial repetition on cognitive response and message acceptance.", *Journal of Consumer Research*, 9, 1 56-65.

Berry, Leonard L., Ruth N. Bolton, Cheryl H. Bridges, Jeffrey Meyer, A. Parasuraman, and Kathleen Seiders. (2010), "Opportunities for innovation in the delivery of interactive retail services." *Journal of Interactive Marketing*, 24, 2 155-167.

Box, George EP, and George C. Tiao. (1975), "Intervention analysis with applications to economic and environmental problems." *Journal of the American Statistical association*, 70, 349 70-79.

Box, George EP, Gwilym M. Jenkins, Gregory C. Reinsel, and Greta M. Ljung. (2015), *Time series analysis: forecasting and control*. John Wiley & Sons.

Brodie, Roderick J., Ana Ilic, Biljana Juric, and Linda Hollebeek. (2013), "Consumer engagement in a virtual brand community: An exploratory analysis." *Journal of Business Research*, 66, 1 105-114.

Cacioppo, John T., and Richard E. Petty. (1979), "Effects of message repetition and position on cognitive response, recall, and persuasion." *Journal of personality and Social Psychology*, 37, 1 97-109.

Chevalier, Judith A., and Dina Mayzlin. (2006), "The effect of word of mouth on sales: Online book reviews." *Journal of marketing research*, 43, 3 345-354.

Chiou, Jyh-Shen, and Cathy Cheng. (2003), "Should a company have message boards on its web sites?." *Journal of Interactive Marketing*, 17, 3 50-61.

Chung, Cindy, and James W. Pennebaker. (2007), "The psychological functions of function words." in *Social communication*, 343-359.

Davidow, M. (2000). The bottom line impact of organizational responses to customer complaints. *Journal of hospitality & tourism research*, 24(4), 473-490.

Dellarocas, Chrysanthos. (2003), "The digitization of word of mouth: Promise and challenges of online feedback mechanisms." *Management science*, 49, 10 1407-1424.

Dellarocas, Chrysanthos. (2006), "Strategic manipulation of internet opinion forums: Implications for consumers and firms." *Management science*, 52, 10 1577-1593.

Dholakia, Utpal M., Vera Blazevic, Caroline Wiertz, and René Algesheimer. (2009), "Communal service delivery: How customers benefit from participation in firm-hosted virtual P3 communities." *Journal of Service Research*, 12, 2 208-226.

Fournier, Susan, and Jill Avery. (2011), "The uninvited brand." *Business horizons*, 54, 3 193-207.

Geylani, Tansev, J. Jeffrey Inman, and Frenkel Ter Hofstede. (2008), "Image reinforcement or impairment: The effects of co-branding on attribute uncertainty." *Marketing Science*, 27, 4 730-744.

Ghosh, T. (2017). Managing Negative Reviews: The Persuasive Role of Webcare Characteristics. *Journal of Internet Commerce*, 16(2), 148-173.

GlobalWebIndex. (2015), *GlobalWebIndex's quarterly report Q2 on the latest trends in social* *networking*, Trendstream Limited, London.

Gluckman, Robert L. (1986), "A consumer approach to branded wines." *European Journal of Marketing*, 20, 6 21-35.

Goh, Khim-Yong, Cheng-Suang Heng, and Zhijie Lin. (2013), "Social media brand community and consumer behavior: Quantifying the relative impact of user-and marketer-generated content." *Information Systems Research*, 24, 1 88-107.

Gummerus, Johanna, Veronica Liljander, Emil Weman, and Minna Pihlström. (2012), "Customer engagement in a Facebook brand community." *Management Research Review*, 35, 9 857-877.

Hennig-Thurau, Thorsten, Edward C. Malthouse, Christian Friege, Sonja Gensler, Lara Lobschat, Arvind Rangaswamy, and Bernd Skiera. (2010), "The impact of new media on customer relationships." *Journal of service research*, 13, 3 311-330.

Hoffman, Donna L., and Thomas P. Novak. (2011), "Marketing Communication in a Digital Era-Marketers should focus efforts on emerging social, mobile and local trends." *Marketing Management*, 20, 3 36-44.

Hofstede, A., van Hoof, J., Walenberg, N., and de Jong, M. (2007). Projective techniques for brand image research. Qualitative Market Research: An International Journal, 10(3), 300–309.

Homburg, Christian, Laura Ehm, and Martin Artz. (2015), "Measuring and managing consumer sentiment in an online community environment." *Journal of marketing research*, 52, 5 629-641.

Hong, J. Y., & Lee, W. N. (2005). Consumer complaint behavior in the online environment. *Web systems design and online consumer behavior*, New Jersey, 2005, 90-105.

Kalwani, M.U. and Narayandas, N., 1995. Long-Term Manufacturer-Supplier Relationships: Do They Pay Off for Supplier Firms? *Journal of Marketing*, *59*, pp.1-16.

Kaplan, Andreas M., and Michael Haenlein. (2010), "Users of the world, unite! The challenges and opportunities of Social Media." *Business horizons*, 53, 1 59-68.

Kerkhof, Peter, Camiel Beukeboom, and Sonja Utz. (2010), "The humanization of a company: effects of personal vs. impersonal organizational reactions to negative online consumer reviews." *Etmaal voor de Communicatiewetenschap, Gent, Belgium*.

Klein, Jill Gabrielle, N. Craig Smith, and Andrew John. (2004), "Why we boycott: Consumer motivations for boycott participation." *Journal of Marketing*, 68, 3 92-109.

Lamberton, Cait, and Andrew T. Stephen. (2016), "A thematic exploration of digital, social media, and mobile marketing: research evolution from 2000 to 2015 and an agenda for future inquiry." *Journal of Marketing*, 80, 6 146-172.

Lee, Young Lyoul, and Seokwoo Song. (2010), "An empirical investigation of electronic word-of-mouth: Informational motive and corporate response strategy." *Computers in Human Behavior*, 26, 5 1073-1080.

Marquaridt, Donald W. (1970), "Generalized inverses, ridge regression, biased linear estimation, and nonlinear estimation." *Technometrics*, 12, 3 591-612.

Mason, Robert L., Richard F. Gunst, and James L. Hess. (2003), *Statistical design and analysis of experiments: with applications to engineering and science*. John Wiley & Sons.

McColl-Kennedy, Janet R., Beverley A. Sparks, and Doan T. Nguyen. (2011), "Customer's angry voice: Targeting employees or the organization?." *Journal of Business Research*, 64, 7 707-713.

Menard, Scott. (1995), "Applied logistic regression analysis. Quantitative applications in the social sciences, No. 106." *Thousand Oaks, CA & London: Sage*.

Mischel, Walter, and Yuichi Shoda. (1999), "Integrating dispositions and processing dynamics within a unified theory of personality: The cognitive-affective personality system.", in *Handbook of personality: Theory and research*, 197-218.

Muntinga, Daniël G., Marjolein Moorman, and Edith G. Smit. (2011), "Introducing COBRAs: Exploring motivations for brand-related social media use." *International Journal of advertising*, 30, 1 13-46.

Neter, John, William Wasserman, and M. G. Kutner. (1989), "Applied linear regression analysis." *Homewood, IL: Irwin*.

Nijssen, Edwin, Jagdip Singh, Deepak Sirdeshmukh, and Hartmut Holzmüeller. (2003), "Investigating industry context effects in consumer-firm relationships: preliminary results from a dispositional approach." *Journal of the Academy of Marketing Science*, 31, 1 46-60.

Pennebaker, James W., Ryan L. Boyd, Kayla Jordan, and Kate Blackburn. (2015), *The development and psychometric properties of LIWC2015*. Technical report, University of Texas at Austin.

Rishika, Rishika, Ashish Kumar, Ramkumar Janakiraman, and Ram Bezawada. (2013), "The effect of customers' social media participation on customer visit frequency and profitability: an empirical investigation." *Information systems research*, 24, 1 108-127.

Schamari, Julia, and Tobias Schaefers. (2015), "Leaving the home turf: how brands can use webcare on consumer-generated platforms to increase positive consumer engagement." *Journal of Interactive Marketing*, 30 20-33.

Schlosser, Ann E. (2005), "Posting versus lurking: Communicating in a multiple audience context." *Journal of Consumer Research*, 32, 2 260-265.

Seraj, Mina. (2012), "We create, we connect, we respect, therefore we are: intellectual, social, and cultural value in online communities." *Journal of Interactive Marketing*, 26, 4 209-222.

Schau, Hope Jensen, Albert M. Muñiz Jr, and Eric J. Arnould. (2009), "How brand community practices create value." *Journal of marketing*, 73, 5 30-51.

Sparks, Beverley A., and Victoria Browning. (2010), "Complaining in cyberspace: The motives and forms of hotel guests' complaints online." *Journal of Hospitality Marketing & Management*, 19, 7 797-818.

Supphellen, M. (2000). Understanding core brand equity: Guidelines for in-depth elicitation of brand associations. International Journal of Market Research, 42(3), 319–338.

Tausczik, Yla R., and James W. Pennebaker. (2010), "The psychological meaning of words: LIWC and computerized text analysis methods." *Journal of language and social psychology*, 29, 1 24-54.

Taylor, David G., Jeffrey E. Lewin, and David Strutton. (2011), "Friends, fans, and followers: do ads work on social networks?." *Journal of advertising research*, 51, 1 258-275.

United Nations Statistics Division. (2008), *International Standard Industrial Classification of All Economic Activities (ISIC), Revision 4.* United Nations, New York.

van Laer, Tom, and Ko De Ruyter. (2010), "In stories we trust: How narrative apologies provide cover for competitive vulnerability after integrity-violating blog posts." *International Journal of Research in Marketing*, 27, 2 164-174.

van Noort, Guda, and Lotte M. Willemsen. (2012), "Online damage control: The effects of proactive versus reactive webcare interventions in consumer-generated and brand-generated platforms." *Journal of Interactive Marketing*, 26, 3 131-140.

Vermeulen, Ivar E., and Daphne Seegers. (2009), "Tried and tested: The impact of online hotel reviews on consumer consideration." *Tourism management*, 30, 1 123-127.

Vivek, Shiri D., Sharon E. Beatty, and Robert M. Morgan. (2012), "Customer engagement: Exploring customer relationships beyond purchase." *Journal of Marketing Theory and Practice*, 20, 2 122-146.

Willemsen, Lotte, Peter C. Neijens, and Fred A. Bronner. (2013), "Webcare as customer relationship and reputation management? Motives for negative electronic word of mouth and their effect on webcare receptiveness." in *Advances in Advertising Research*, 9, 55-69. Springer Fachmedien Wiesbaden.

Wirtz, J., & Mattila, A. S. (2004). Consumer responses to compensation, speed of recovery and apology after a service failure. *International Journal of service industry management*, 15(2), 150-166.

Conclusion to paper II

The third paper of the thesis contributes to further our understanding of the dynamics of webcare interventions in consumer conversations on Facebook brand pages. Supported by large field data from consumer conversations and brand replies on Facebook brand pages including diverse webcare strategies (reactive, proactive, single, multiple, personal, impersonal, early and late), paper II provides meaningful insights into how webcare interventions affect consumer conversations. Understanding how webcare interventions influence consumer conversations helps marketers plan and execute adequate webcare strategies when needed. Key results that are of particular managerial interest include the positive cumulative effect of multiple webcare interventions, the negative effect of reactive webcare interventions compared to proactive ones, the positive effect of personalizing webcare interventions as well as the importance of critical timing of brand interventions. The results also shed light on the dynamics over time of the effect of webcare interventions on consumer conversations, starting with a strong immediate effect, followed by a rapidly decaying effect.

Overall, paper II helps marketers to effectively manage consumer conversations on Facebook brand pages. While this second paper explores the effects of brand interventions (webcare interventions) in consumer-to-consumer conversations driven by the need to mitigate negative conversations and bolster positive ones, the third paper focuses on the mechanisms of emotional contagion from brands to consumers and among consumers by exploring how brands can influence emotionally on consumers and how consumers can influence emotionally on each other.

Chapter 4: Introduction to paper III

The third and final paper in the thesis, entitled “Emotional Dynamics on Facebook Brand Pages” investigates the emotional dimension of consumer-brand relationships on Facebook brand pages. In this paper, emotional contagion is regarded as a fundamental pillar of emotional branding on social media. Understanding how emotional contagion operates on Facebook brand pages is crucial for marketers to design and implement successful emotional branding strategies. An empirical analysis of the emotional dynamics of consumer and brand engagement was conducted, drawing on emotional branding and contagion research. The paper examines the emotions conveyed in 317,357 brand posts, 83,310,772 consumers' reactions to brand posts, 41,158,070 consumer comments and 14,482,369 consumer replies to comments, collected from 942 Facebook brand pages. Results shed light on which emotions are contagious from brands to consumers and among consumers, whether the valence and arousal of emotions determine their contagiousness, and how combined emotions can interact to amplify or attenuate emotional contagion on Facebook brand pages.

This paper builds on experiences acquired from two previous papers published in the Australian and New Zealand Marketing Academy Conference (ANZMAC) and the 6th Global Innovation and Knowledge Academy (GIKA) in 2016. The ANZMAC paper was also selected to be published in the Journal of Consumer Marketing. Both papers are authored by Chedia Dhaoui, Cynthia M. Webster and LayPeng Tan with the same contribution ratio as the thesis paper (outlined in the Acknowledgments section) and are included in Appendix B, C and D. Emotional Dynamics on Facebook Brand Pages is targeted for submission to the Journal of Consumer Research. The paper is presented in this thesis in the journal's required publication format yet for ease of reading tables and figures are embedded throughout. The contribution ratio for this paper is outlined in the Acknowledgements section of the thesis.

Emotional dynamics on Facebook Brand Pages

Chedia Dhaoui, Macquarie University, Australia, chedia.dhaoui@mq.edu.au

Cynthia M. Webster, Macquarie University, Australia, cynthia.webster@mq.edu.au

LayPeng Tan, Macquarie University, Australia, laypeng.tan@mq.edu.au

Abstract

In the quest of creating strong relationships with valuable consumers, brands invest heavily in developing emotional branding strategies. Emotional branding, where companies communicate emotional value-laden content, provides an effective means to forge an enduring emotionally evocative relationship between consumers and brands. This paper tackles the emotional perspective of consumer and brand engagement on Facebook brand pages and is one of the first studies to consider multiple types of emotions rather than single dimension sentiment scale. It is also one of the first to take emotional icons into account as well as Facebook's emotional reactions to assess emotional contagion from actual Facebook data. Drawing on emotional branding and contagion research, this paper examines the dynamics of 317,357 brand posts containing 83,310,772 consumer emotional reactions embedded within 41,158,070 consumer comments and 14,482,369 consumer replies to comments collected from 942 Facebook brand pages. Results shed light on which emotions are contagious from brands to consumers and among consumers, whether the valence and arousal of emotions determine their contagiousness, and how combined emotions interact to amplify or attenuate emotional contagion on Facebook brand pages.

Keywords: Emotional dynamics; Emotional contagion; Online branding; Facebook brand pages.

INTRODUCTION

Brand marketers strive to create strong and sustainable relationships with their consumers as a means of ensuring their retention and achieving long-term profitability. In the branding context, Fournier (1998) points out that investigating the emotional dimension of consumer-brand relationships is of high interest to marketing academics and practitioners as emotional attachment to the brand leads to greater brand commitment (Thomson et al, 2005), and contributes to consumer brand relationship durability over time (Fournier, 1998). Other researchers (Gobé, 2001, Atkin, 2004; Lynch and De Chernatony, 2004; Lindstrom, 2005) also claim that the emotional facet of brand-consumer relationships is highly regarded as a fundamental pillar of brand differentiation in the marketplace leading to a sustainable competitive advantage. In this regard, emotional branding where companies communicate emotional value-laden content is believed to attract consumers and stimulate affective responses to establish intimate and lasting emotional connections between consumers and the brand (Roberts 2004). Although previous research recognizes the emotional dimension of consumer brand engagement (Hollebeek, Glynn and Brodie, 2014; Dessart et al. 2016), many studies examine the behavioral dimension of engagement (van Doorn et al. 2010; Verhoef, Reinartz and Krafft, 2010; Jaakkola and Alexander, 2014; Gummerus et al. 2012; Schivinski, Christodoulides and Dabrowski, 2016) and do not tackle emotions as the main focus of their study.

Despite the considerable research on the spread of emotions between employees and customers (e.g. Pugh, 2001), and among co-workers (e.g. Barsade, 2002), to the best of our knowledge, no study so far has examined the emotional contagion from brands to consumers and among consumers on social media. Although a few studies investigate online emotional contagion, they predominantly focus on emotional contagion among users of social media platforms not on the branding context. Some work has demonstrated that emotional contagion occurs among friends on Facebook (Kramer, Guillory and Hancock, 2014) and among Twitter users (Ferrara and Yang, 2015). Other work has found that emotions expressed via smileys are transferred among people through emotional contagion (Lohmann, Pyka and Zanger, 2017). However, much of the emotional contagion research is based on online experiments, which research shows may artificially inflate results (van Reijmersdal, Neijens and Smit, 2007).

An angle that remains under-researched is the extent to which emotional branding initiated by the brand, understood and embraced by consumers then propagated among consumers on social media contributes to fueling emotional contagion. There is also a lack of studies examining longitudinal data of actual brand-to-consumer and consumer-to-consumer interactions to demonstrate the occurrence of emotional contagion, particularly on Facebook brand pages.

The current paper looks at the phenomenon of emotional contagion on Facebook brand pages by which emotions propagate from the brand-to-consumers or from one consumer to another. To the best of our knowledge, the present research is one of the first attempts to examine how emotional branding initiated by the brand leads to emotional interactions with consumers and emotional contagion among consumers on social media using a large, longitudinal dataset. The co-occurrence of two different emotional contagion mechanisms is explored, one from brands to consumer (B2C), and the other among consumers (C2C). As such, this paper contributes to the stream of research on emotional contagion by examining the co-occurrence of these two mechanisms of emotional contagion on Facebook brand pages. Furthermore, this research is one of the first to examine the contagious effects of multiple emotions. Indeed, the contagion effects of five emotions (Love, Happiness, Anger, Sadness, Surprise), matching the emotional reactions supported by Facebook, are assessed. By examining the contagion of combined emotions, we can identify the different emotional patterns occurring in the data, and their combined effects. This contributes to further our understanding of the interaction of several emotions in the brand and consumers' emotional content, and its impact on their contagiousness. In particular, the current paper seeks to provide answers to the following questions:

- Does emotional contagion occur between brands and consumers as well as among consumers on Facebook brand pages? If so, what are the emotions that are most contagious? How does valence and arousal of emotions contribute to its contagion effect?
- Are there any interaction effects of combined multiple emotions? If so, what are the patterns of combined emotions that either improve or diminish the contagion effect of specific emotions? In other words, how can each emotion interact with and influence other emotions and what is the outcome in terms of contagiousness?

To address these questions, two empirical studies examine a unique data set of 317,357 brand posts containing 83,310,772 consumers' emotional reactions embedded within 41,158,070 consumer comments and 14,482,369 consumer replies to comments collected from 942 Facebook brand pages. Facebook is a suitable online context for this research as it supports the creation of multi-way relationships between brands and consumers and among consumers within the brand community. Facebook is one of the largest and most widely used platforms for online conversations connecting over 2 billion monthly active consumers in June 2017. Moreover, compared to Twitter connections, Facebook connections carry a higher emotional contagion power (Kwak et al. 2010).

The rest of the paper proceeds as follows. The first section presents the conceptual background, focusing on emotional branding and emotional contagion on social media and developing the research questions. Then, to address the research questions, we conduct two empirical studies. Study 1 examines whether emotional contagion occurs from brands to consumers (B2C) on Facebook brand pages and investigates which emotions are the most contagious in B2C interactions. Study 1 also evaluates the interaction effects of combined multiple emotions and the patterns of combined emotions that either improve or diminish the contagion effect of specific emotions. Study 2 examines whether emotional contagion occurs among consumers in consumer-to-consumer (C2C) conversations on Facebook brand pages, identifies which emotions are contagious and whether they differ from those emotions that are contagious from brand-to-consumers. The paper concludes with a discussion of the results, managerial implications and suggestions for future research avenues in this area.

CONCEPTUAL BACKGROUND

Emotional branding on social media

Today social media is an integral part of online branding. A great deal of social media marketing content is emotionally loaded to better connect with consumers and influence their perceptions, thoughts and feelings towards the brand - the so-called emotional branding. Emotional branding refers to the engagement of consumers in a deep, long-term, intimate connection with the brand (Morrison and Crane, 2007). Emotional branding is also considered as a “consumer-centric, relational, and story-driven approach to forging deep and enduring affective bonds between consumers and brands” (Thompson, Rindfleisch, and Arsel 2006, p.50). The emotional branding perspective suggests that firms ought to concentrate on forging strong and meaningful emotional bonds that proactively enrich consumers' lives, become part of their memories and social networks (Thompson, Rindfleisch, and Arsel 2006). As a response to emotional branding, consumers praise or complain about the brand, behaviors strongly shaped by emotions. Such responses, in turn, affect other consumers' engagement and feelings towards the brand thanks to the virality of online social networks.

Emotional Contagion on social media

Schoenewolf (1990, p.50) considers emotional contagion as “a process in which a person or group influences the emotions or behavior of another person or group through the conscious or unconscious induction of emotion states and behavioral attitudes”. This applies to automatic and non-conscious mimicry in which individuals spontaneously mimic others’ emotions via non-verbal cues such as facial expressions (Dimberg 1982; Lundqvist and Dimberg 1995), postural or body language (Bernieri 1988; Chartrand and Bargh 1999), speech patterns (Ekman, Friesen and Scherer 1976). This mimicking behavior leads individuals to experience an emotional convergence via a feedback reaction (Lohmann, Pyka and Zanger, 2017) where the receiver experiences the same emotional state as the sender (Adelmann and Zajonc 1989). Along these lines, emotional contagion arguably occurs during interactions when the actors involved in the relationships converge emotionally (Hatfield, Cacioppo and Rapson, 1994).

Does emotional contagion occur on Facebook brand pages?

By deploying online emotional branding strategies, marketers do not simply wish consumers to catch the same emotions displayed in the brand posts, but more importantly to pass them along to other consumers. The ubiquity of Facebook as a social media platform is believed to facilitate the emotional contagion between the brand and its consumers as well as among brand community members and beyond. Does emotional contagion occur on Facebook brand pages? Does it occur both between the brand and the consumers among consumers? We propose to address these questions in this paper.

Emotional contagion through in-person interactions is well established (Fowler and Christakis, 2008), early research shows emotional contagion also occurs among users via online interactions on social media platforms despite the lack of “non-verbal cues typical of in-person interactions” (Ferrara and Yang, 2015, p.1). For example, Kramer, Guillory and Hancock (2014) demonstrate through a large scale experiment that emotional contagion operates through online computer mediated communications among friends on Facebook. The authors show that when people are exposed to less positive content produced and shared by friends on their newsfeed, they tend to create fewer positive content and more negative posts. The authors conclude that text-based communication is an efficient way to transmit emotions (Kramer, Guillory and Hancock 2014). Other research by Coviello et al., (2014) demonstrates that emotional contagion can occur on a large scale across the Facebook social network. The authors analyze user posts on Facebook and find that the emotional content posted by Facebook users affects the posts of their friends. Although, these studies are among the very few to demonstrate the occurrence of emotional contagion on Facebook, their findings are limited to the emotional contagion among friends on Facebook and do not apply to the branding context.

Social psychology theory ‘common bond attachment’ (Ren et al. 2007) emphasizes that one of the reasons why members belong to a community is that they feel socially and emotionally attached to one another and this leads to the development of close relationships to particular community members. Indeed, within the same online community, members interact with other members and share information creating ongoing social interactions (Ren et al. 2007), mutual sympathy among members (Collins and Miller 1994) and strong social bonds (Buchan, Croson and Johnson 2006). Algesheimer, Dholakia and Herrmann (2005) consider that by belonging to the brand community, consumers strengthen their relationships with other members through “brand community identification”. This creates a collective or a common identity (Battacharya and Sen 2003) which encompasses an emotional component capturing ‘consumer’s affective commitment’ to the group (Ellemers, Kortekkas, and Ouwerkerk 1999), a sense of consumer’s emotional involvement with other community members (Algesheimer, M. Dholakia and Herrmann 2005), or an affective commitment to the community (Tsai and Bagozzi, 2014). Furthermore, Marzocchi, Morandin and Bergami (2013) show that members of a brand community not only identify to the community itself but also to the brand.

Emotional valence and emotional contagion

On Facebook brand pages, brand posts can display positive or negative emotions. Intuitively, one would assume that positive (negative) emotions displayed in brand posts would induce positive (negative) emotions in consumers’ comments via B2C interactions. Consumers can also express positive and/or negative emotions in their comments that would arguably transfer to other consumers via C2C interactions. In either B2C or C2C emotional contagion, which is more likely to be contagious – positive or negative emotions?

Research in psychology indicates that negative information is more memorable, more diagnostic and processed more thoroughly (Fiske, 1980; Pratto and John, 1991; Baumeister et al., 2001). Consistent with the assumption of a negativity effect (Ito et al., 1998), many researchers show that, compared to positive emotions, negative emotions exert a stronger influence on relationships (Gottman and Levenson, 1986). Indeed, Levenson and Gottman (1985) find that the two partners' "reciprocity" of negative emotions during their interactions is more potent than the reciprocity of positive emotions. Barsade' research (2002) on emotional contagion and its influence on group dynamics in organizations, however, empirically demonstrates that the valence of emotions has no effect on its contagiousness among individuals and that contagion of positive emotions is just as prevalent as contagion of negative emotions. Other studies contradict these findings and show an asymmetric effect of positive and negative emotions, with positive emotions exerting a stronger contagion effect than negative emotions. For example, in one of the few studies on the virality of online emotional content, Berger and Milkman (2012) find that positive emotional content is more shared among people than negative content. The authors suggest that positive emotional content is more shared because it communicates the identity of the sender and indicates the sender is a positive person, someone who likes to encourage others and "… makes others feel good" (Berger and Milkman, 2012, p.2). This is consistent with Wojnicki and Godes' (2008) research who claim that consumers often pass along emotional content because of "self-presentation".

To explain the asymmetric effect of positive and negative emotions, Isen (1984) argues that individuals who experience positive emotions often tend to focus on the positive side of the stimulus to which they are exposed and seek to maintain their positive emotional state, while those who are experiencing negative emotions tend to neglect the stimuli inducing the negative emotions and attempt to end their current negative emotional state. In this vein, Cialdini and Kenrick (1976) propose a model of negative state relief suggesting that individuals experiencing temporary negative emotional state are motivated to engage in “altruistic” behavior to decrease their negative mood state. Mitchell et al. (2001) provide an explanation for that in claiming that generally people who are experiencing unpleasant emotional states do not enjoy negative feelings and attempt “to distract themselves from unpleasant thoughts, and engage in other activities that divert their attention from the stimuli that caused them to experience unpleasant affect” (Mitchell et al. 2001, p.349).

Emotional arousal and emotional contagion

Many researchers indicate that emotional contagion is not only driven by its valence, but also by the intensity with which emotions are expressed, capturing the physiological arousal of emotions. Early research points out that emotional arousal plays a crucial role in the transmission of emotional states among individuals working in a group (Barsade, 2002). According to Watson and Tellegen (1985) and Barrett and Russell (1998), happiness is a positive emotion associated with joy, peacefulness and serenity with low arousal, sadness is a negative emotion characterized by low arousal and ‘anger’ is a negative emotion with high arousal. This claim is also highlighted by Berger and Milkman (2012), who consider that while anger captures a negative emotional state with “heightened arousal or activation”, sadness reflects an emotional state with a low arousal. Finally, ‘love’ denotes a positive emotional state with high arousal (Batra, Ahuvia and Bagozzi, 2012).

Berger and Milkman (2012) consider that the contagiousness of emotional content relies on the “activation in social transmission”, which delineates the activation that emotions evoke (Smith and Ellsworth, 1985). The authors claim that the contagiousness of emotions of the same valence (e.g. love/ happiness, anger/sadness), may differ because they induce different levels of arousal (Smith and Ellsworth, 1985). Barsade (2002) associates arousal to emotional energy and posits that a high energy expression of an emotion leads to a stronger contagion effect than a low energy expression of the same emotion. In this vein, Robinson and McArthur (1982), indicate that individuals who express their emotional states more forcefully, or expressively (Friedman et al., 1980) are better noticed by others and therefore, more likely to increase the exposure and spread of emotions.

In examining the effects of arousal on the contagiousness of emotions, the findings of prior research are contradictory. While Barsade (2002) finds no effect of arousal on the contagiousness of emotions, Berger and Milkman (2012) find that highly arousing emotional content is the most shared. Building on previous research, we aim to address the following question: Are high arousal emotions more contagious than low arousal emotions?

Contagion effects of combined emotions

Another interesting factor driving emotional contagion, which is underexplored and merits further investigation, is the combination of multiple emotions. Previous research on emotional contagion predominately focuses on the contagiousness of a single emotion, whether positive or negative, high arousal or low arousal, and remains silent on the spread of combined emotions. To fill this void, the current research examines the contagiousness of both single and combined emotions on Facebook brand pages.

As pointed out by Izard (2013), emotions can interact and form patterns of emotions. While the combination of emotions does not change each fundamental emotion's "essential or genotypical properties" (Izard, 2013, p. 4), their "interactional effects and the consequent observable behavior may differ in different patterns" (Izard, 2013, p. 4). In this research, we aim to examine the interaction effects of combined emotions and their impact on emotional contagion. For instance, we aim to shed light on whether one emotion can amplify or attenuate the contagion effect of another emotion. Furthermore, the key managerial interest of this work is arguably to attenuate the contagious effect of a negative brand communication (brand posts) by combining its negative emotion with positive ones. This applies to cases, for example, when a brand announces fundamentally negative news (e.g. product recall) and incorporates additional emotions in the brand post to attenuate the potential contagion effect of the negative emotion. Along these lines, we propose to address the following questions:

- Does the contagiousness of an emotion get intensified when combined with another emotion of the same valence?
- Does the contagiousness of an emotion get attenuated when combined with another emotion of opposite valence?
- Does the contagiousness of an emotion get intensified when combined with a higher arousal emotion?
- Does the contagiousness of an emotion get attenuated when combined with a lower arousal emotion?

STUDY 1: B2C EMOTIONAL CONTAGION

The objective of study 1 is three-fold. First, we examine whether emotional contagion occurs from brands to consumers (B2C) on Facebook brand pages. Second, we investigate which emotions are the most contagious in B2C interactions. Third, we evaluate the interaction effects of combined emotions and the interaction effects that can either improve or diminish the contagion effect of specific emotions. The data used in this study consists of brand posts on Facebook brand pages and their associated consumers' emotional reactions.

Data

Data were collected from 942 Facebook brand pages among the most talked about on the social network. The selected brands were among those listed on fanpagelist.com, a website reporting the top brands on Facebook. They span across 16 industry categories including airline, automotive, college/university, cruise, dining, event, food/beverage, lodging, media, nonprofit, retail, services, sports, technology, and travel. Data collection was conducted using Facebook Graph API, a programmable data access service allowing researchers to request and download large amounts of content from Facebook. The gathered data covered brand posts (i.e. brand generated content posted on Facebook brand pages) and consumers' emotional reactions to the brand posts. The data covered a one-year period from 30th June 2016 to 30th June 2017. Five emotions (i.e. love, happiness, sadness, anger and surprise) were identified in brand posts as well as in consumers' emotional reactions. The resulting dataset consists of 317,357 brand posts totaling 83,310,772 consumers' emotional reactions.

Classification of emotions in brand posts

On Facebook brand pages, brand marketers can convey emotions via verbal communication (text) and non-verbal communication (images, videos). Three classification methods were used to identify emotions in brand posts: (1) Artificial Intelligence (AI)-enabled visual analysis of photos and videos posted by the brands on Facebook, (2) Unicode character analysis to identify emotional icons (emoticons and emojis) in brand posts, and (3) Machine Learning emotion classifier to identify emotions in text-based brand content.

AI-detected visual emotions

Given 77% of all collected brand posts were visual (141,665 photos and 102,588 videos), it is important to identify the emotions embedded in visual content. A typical approach to classify visual content into a set of emotions consists of manually coding each image or video using a taxonomy of human facial expressions such as the facial action coding system (FACS) (Ekman, Friesen and Hager, 2002). Without a common and comprehensive coding scheme such as FACS, manual coding would rely on coders’ own interpretations of the contents which can lead to biases due to differences in coders’ interpretations. However, even with a pre-determined coding scheme, and assuming all coders concur, a major limitation is the time required to train human experts to use FACS to manually annotate images and videos (Burgoon et al 2017). Furthermore, manual coding is an onerous process and impractical for very large datasets to categorize. Therefore, automated methods to detect emotions from visual content were considered.

AI-enabled Cognitive Services from Microsoft Azure Cloud services are intelligent algorithms capable of analyzing natural methods of communication including text, audio, images and videos. Emotion API, part of Microsoft's Cognitive Services, reliably detects emotions shown in facial expressions embedded in visual content. According to Ekman and Friesen (1971), there exists a set of facial expressions universally understood across cultures and have little to no ambiguity as to which emotions they are associated. These include facial expressions such as anger, contempt, disgust, fear, happiness, sadness and surprise, all of which are detectable using Microsoft's Emotion API. For this study these seven facial expressions provide a robust framework to classify emotions featured in the visual content. As illustrated in *Figure 4* each face detected by Emotion API is associated with a set of probabilities corresponding to each of the seven emotions. These probabilities are produced by the AI-enabled visual analysis used by Emotion API to evaluate facial expressions. When a photo or video contains multiple faces, the maximum probability of each emotion is retained. This means that for each brand post, the probability of occurring of each emotion among the seven supported emotions is produced. The higher the probability, the likely the detection is accurate. In this paper, we decided that when the probability of an emotion exceeds 0.9, the brand post is considered as conveying such emotion. Note that a brand post can potentially convey several emotions, each of which scores a probability exceeding 0.9.

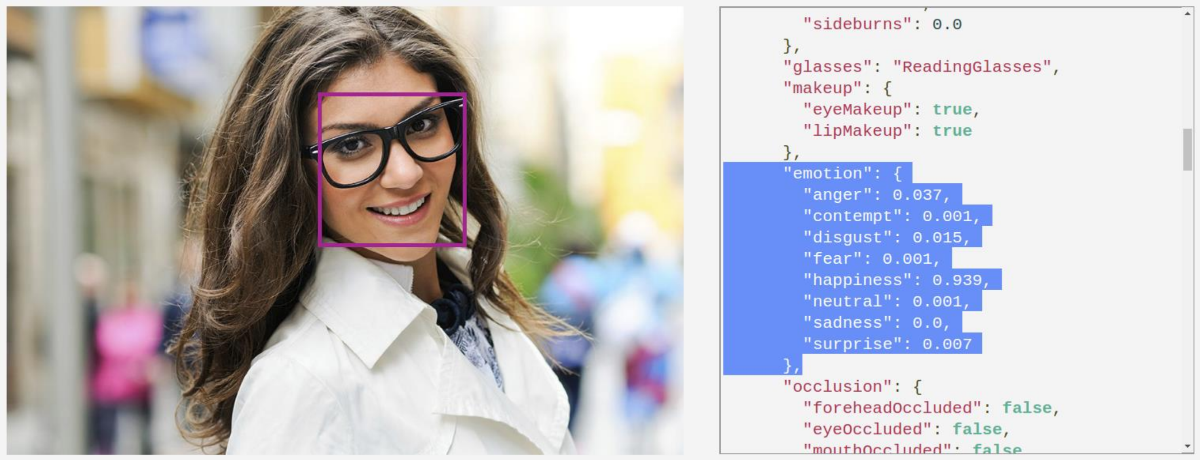


Figure 4. Example of face detection and visual emotion analysis using Microsoft Cognitive Services (source: https://azure.microsoft.com/en-au/services/cognitive-services/face/)

Among the collected brand posts, 141,665 photos posts were analyzed by Emotion API. For video posts, the thumbnail images were analyzed. A video thumbnail is a static image displayed before a video starts playing and is typically selected by the video producer (e.g. the brand marketers) as representative of the video content. To improve the reliability of the emotional analysis of each video, an additional 20 frames (images) extracted at equally spread time-frames within each video were also analyzed. Note that the choice of 20 frames was arbitrary, but does substantially increase the amount of the video content covered. The resulting outcome was a dataset of 1,603,511 images of which 554,197 human faces were identified and analyzed.

Emotional Icons

While Park, Chung and Rutherford (2011) note that online text-based computer mediated communication is replacing traditional human interaction, Evans (2017) argues that in the absence of rich face-to face interactions, digital text alone is “impoverished and, on occasion, emotionally arid” (p.32). Emotional icons contribute considerably to strengthen the message in written interaction (Skovholt et al., 2014). Emotional icons capture the non-verbal-cues via 2D visual static or animated graphics reflecting brands’ and consumers’ emotional states in the form of smiley faces, love hearts, and emoticons. Baron (2000) considers emotional icons as “emotion markers” (p. 242), effectively replacing facial expressions (Lohmann, Pyka and Zanger, 2017), and functioning similarly to “gesture, body language and intonation in spoken interaction” (Evans, 2017, p.33). Emotional icons enrich online content with emotional meaning (Skovholt, Grønning and Kankaanranta, 2014) and create friendly and more harmonious interactions (Dercks et al., 2007; Cheshin, Rafaeli and Bos, 2011). Despite the considerable importance given to emotional icons in online interactions, no study so far has investigated the use of these icons in driving emotional contagion on Facebook brand pages.

In this paper, we analyzed emotional icons (e.g. emoticons, smileys and love characters) as emotional conveyors and drivers of emotional contagion from brand-to-consumers, and from consumer-to-consumer. There are sets of emotional icons associated with specific emotions on Facebook, as illustrated in *Table 5*. Such emotional icons are represented in the data as special characters using the Unicode standard for encoding symbols or icons. We classified text into each emotional category (love, happiness, sadness, anger and surprise) based on whether the Unicode characters of the corresponding emotional icons were found in the text. For example, text containing at least one of the happy emotional icons (e.g. 😀😁😂😃😄😅😆...) was classified as happy. Furthermore, a text can be associated as conveying multiple emotions if emotional icons of different emotions are identified. Finding whether a text contains any emotional icons was performed using regular expressions in the R statistical package (version 3.4.2).

Table 5. Emotional icons and their associated emotions in Facebook’s smiley and people icons

Emotion	**Emoticons**
Love	😍😘😗😙😚💘❤💓💕💖💗💙💚💛💜💝💞💟❣💌
Happiness	😀😁😂😃😄😅😆😉😊😋😎🙂☺😛😜😝

Sadness	🙄😣😥😪😫😒😓😔😕☹️🙁😖😞😟😢😭😦😧😨😩😳
Anger	😡😠
Surprise	😮😲😯

Text-based emotions

Kramer, Guillory and Hancock (2014) have demonstrated that emotional contagion can operate through text-based computer mediated communication among friends on Facebook. Text is arguably the most common form of communication used to transfer emotions through written correspondence. It is a vehicle of emotions through an array of verbal strategies (Fussell, 2002) provided by all languages. However, it can be challenging to identify the emotions expressed in any given text when the language used is not formal, jargon or a mix of multiple languages is used. This is particularly the case on social media where multiple languages coexist and overlap, where formal language is not the norm, and where regular lexical based classification of emotion is not reliable (Kiritchenko et al., 2014). Nevertheless, when text includes an emotional icon such as a smiley or an angry emoticon, it is reasonable to assume that the extracted text alone is likely to expresses the same emotion as the accompanying emotional icons. This also applies to consumer comments in which text contains emotional icons. Based on such assumption, content previously classified using their accompanying emotional icons can be stripped of its emotional icons, retaining only the free form text (if any), and compiled into a large classified dataset of text that can be used as a training dataset for a Machine Learning classifier. The fundamental principal of Machine Learning is to train a model using text that has already been classified using manual classification or other automated classification techniques (e.g. lexicon based classifiers). The training process consists of constructing knowledge from a large set of examples, i.e. the training dataset.

Machine learning models were obtained using gradient boosted trees (Chen & Guestrin, 2016) from the training dataset (one model for each emotion). The obtained models were then used to classify any free form text, including all brand posts complemented by brand generated free form text whether including emotional icons or not. The results are probabilities associated with each emotion. When the probability of an emotion exceeds 0.9, the text being analyzed is considered as conveying the emotion. Note that several emotions can each potentially score a probability above 0.9. In such cases, multiple emotions are associated with the text.

The outcomes of emotion classification of brand content using all of the above three methods are combined into Boolean values (true/false) among a set of seven emotions: love, happiness, anger, contempt, disgust, sadness, and surprise.

Consumers' emotional reactions to emotional brand posts

Facebook has recently released new additional emotional features called “emotional reactions” as an extension to the existing ‘Like’ button, capturing five additional emotions including “love”, “haha”, “wow”, “sad” and “angry” (*Figure 5*). Using these new emotional reactions, consumers are now able to interact directly in responding to the brand post or to other consumers by selecting one of these emotional reactions. This allows consumers to easily engage by just clicking on the emotional reactions rather than typing a comment.

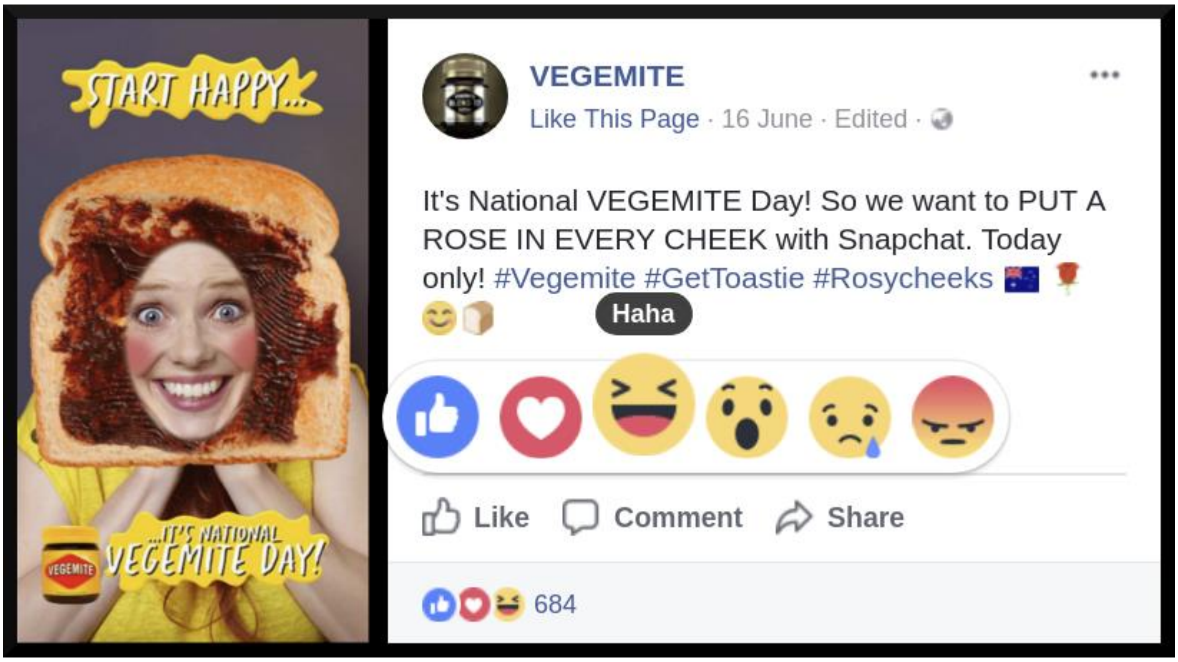


Figure 5. Consumers' emotional reactions on Facebook

B2C emotional contagion

As stated earlier, B2C emotional contagion captures the transfer of emotions from brands to consumers. B2C emotional contagion occurs when emotions displayed in brand posts converge with emotions expressed in consumer comments. Emotional Convergence (EC) is calculated as the number of consumer emotional reactions which converge with the emotion conveyed in the brand post relative to the total number of consumer emotional reactions to the brand post. For each Brand Post BP conveying a set of emotions $\{E_1 \ldots E_n\}$, Emotional Convergence EC is calculated as the proportion of consumer emotional reactions that match at least one emotions conveyed in the brand post.

Results

Descriptive statistics

The combined results of classifying the emotions of all collected brand posts (N=317,357) using all three methods described above show that 84.86% (269,327) of brand posts convey emotions. Descriptive statistics of emotional posts are summarized in *Table 6*. The results indicate that 48.5% of them express happiness, 41.3% express love, 36% express sadness, 24.3% express anger and 20% express surprise. The emotion contempt is detected in a negligible number of brand posts (3 only) and the emotions of fear and disgust have not been detected in any of the brand posts collected. For these reasons, contempt, disgust and fear emotions have been excluded from the remainder of the study. The remaining emotions of "love", "happiness", "sadness", "anger" and "surprise" match the emotional reaction icons provided by Facebook. Furthermore, 54.6% of all brand posts included two or more emotions.

Results in *Table 6* show that text analysis (using Machine Learning) is yet the main mean of detection of emotions in brand posts compared to facial expressions or visual icons. This was expected given the structured nature of language and the advances in natural language processing compared to other forms of automated emotion detection. Furthermore, love, happiness and sadness are among the key emotions expressed using emotional icons. Finally, facial expression in visual brand posts were predominantly conveying happiness, which is also expected given the positive messages brand marketers typically aim to convey.

Table 6. Classification of emotions in brand posts (N=317,357)

Emotional brand posts	Love	Happiness	Sadness	Anger	Surprise	Contempt	Disgust	Fear
Single emotion	23,510	34,353	18,689	11,550	8,022	0	0	0
Proportion single emotion	0.074	0.108	0.059	0.036	0.025	0.000	0.000	0.000
Mixed emotions	107,625	119,671	95,731	65,630	55,556	3	0	0
Proportion mixed emotion	0.339	0.377	0.302	0.207	0.175	0.000	0.000	0.000
Total detected	131,135	154,024	114,420	77,180	63,578	3	0	0
Proportion Total	0.413	0.485	0.360	0.243	0.200	~ 0.000	0.000	0.000
Detected using emoticons	7,060	6,289	4,524	57	146	NA	NA	NA
Detected using visual emotions (faces)	NA	28,082	37	92	255	3	0	0
Detected using Machine Learning (text)	126,752	134,502	111,226	77,063	63,266	NA	NA	NA

Consumers' emotional reactions to brand posts are summarized in *Table 7*. The descriptive statistics indicate that consumers' emotional reactions are primarily those of "love" (59%) followed by "happiness" (15%), "surprise" (13%), "anger" (6%) and "sadness" (6%). Note that brand posts also generate "likes", totaling 179,339,703 which is disproportionate compared to the number of other emotional reactions. One could argue that this might be simply due to the historical nature of the "like" button as it is long established as the first and only reaction icon available until recently. The default display of "like" also makes it the easiest option to select. Furthermore, "like" does not convey a particular emotion but rather reflects an 'agreement', or a 'consensus'. For these reasons, the focus on the paper is on the other specific emotions available as emotional reactions including love, happiness, surprise, anger and sadness.

Table 7. Descriptive statistics of consumers' emotional reactions to brand posts

Emotional reactions	**Love**	**Happiness**	**Surprise**	**Anger**	**Sadness**	**Any emotion**
# obs.	49,029,282	12,738,119	10,774,275	4,677,775	5,384,548	82,603,999
Proportion	0.59	0.15	0.13	0.06	0.06	1.000
Mean per brand post	154.49	40.14	33.95	14.74	16.97	260.29

B2C emotional contagion

To examine the emotional contagion between brands and consumers, we first analyze brand posts conveying a single emotion by performing a two sample t-test for each emotion among love, happiness, sadness, anger and surprise. This evaluates the contagiousness of each emotion separately without interaction effects that take place when a mix of emotions are conveyed in the same brand post. Five groups of brand posts conveying each of the single emotions include 23,510 brand posts conveying love only, 34,353 brand posts conveying happiness only, 18,689 brand posts conveying sadness only, 11,550 brand posts conveying anger only and 8,022 brand posts conveying surprise only. In addition, a group of brand posts not conveying any emotion at all includes 48,030 brand posts. Because the groups do not have the same size, a bootstrap t-test is conducted using the approach described in Efron and Tibshirani (1993) in order to reduce bias. Bootstrapping uses multiple random samples by resampling the original observations with replacement. 5,000 bootstrap samples were used in accordance with the recommendation of Efron (1987) that "on the order of 1000" replications are needed. If an emotion E conveyed in a brand post is contagious, we expect a higher proportion of emotional reactions expressing the same emotion E compared to emotional reactions to brand posts not conveying any emotion at all. The results of the five bootstrap t-tests are reported in *Table 8* along with descriptive statistics for each comparison. The results reveal that four of the five bootstrap t-tests are significant ($p<0.05$) for brand posts conveying happiness, sadness, anger and surprise, indicating that there is a statistically significant difference between each sample and the sample from the reference group.

Nearly all emotions, except one (happiness), scored positive differences against the reference group, providing evidence that emotional contagion occurs from brand-to-consumers (B2C) for the emotions of sadness, anger and surprise on Facebook brand pages. The relative difference is highest for the emotions of anger (+21.98%) and surprise (+11.80%). Interestingly, happiness was found to have a statistically significant negative difference against the reference group (-6.02%). This finding suggests that brand posts conveying happiness do not generate more happy consumer emotional reactions than brand posts conveying no emotions at all.

Table 8. Bootstrap t-tests assessing the emotional contagion from brand-to-consumers

Group (brand posts with a single emotion)	**Love**	**Happiness**	**Sadness**	**Anger**	**Surprise**
B2C emotional Contagion (EC) Mean proportion of consumers' emotional reactions expressing the same emotion as the brand post	0.652	0.078	0.026	0.041	0.125
Reference sample Mean proportion of consumers' emotional reactions expressing the same emotion in response to brand posts conveying no emotions	0.649	0.083	0.024	0.034	0.111
Difference against the reference sample	0.003 (+0.43%)	-0.005 (-6.02%)	0.002 (+9.30%)	0.007 (+21.98%)	0.013 (+11.80%)
Bootstrap t-tests results (based on 5,000 resampling)	**Love vs. No emotion**	**Happiness vs. No emotion**	**Sadness vs. No emotion**	**Anger vs. No emotion**	**Surprise vs. No emotion**
p-value	0.3884 ⛔	0.0016 ✅	0.0278 ✅	<0.001 ✅	<0.001 ✅
t statistic	0.875	-3.278	2.192	5.292	5.596

✅ = significant, ⛔ = not significant

Another finding relates to the t-test of brand posts conveying love, which was not statistically significant, failing to provide evidence of contagiousness of the love emotion from brands to consumers. A possible explanation of this finding could be that love may generate other similar positive emotions such as happiness. A further bootstrap t-test was conducted to confirm or dismiss that possibility by comparing the emotional reactions of happiness to brand posts conveying love and the emotional reactions of happiness to brand posts in the reference group of posts with no emotions. The results show a statistically significant difference ($p<0.05$), however the difference in means is negative (0.079 for brand posts conveying love and 0.083 for brand posts conveying no emotions). This finding suggests that love conveyed in brand posts generates less happiness in consumer reactions than brand posts with no emotions at all. Thus, it is plausible that both love and happiness are too frequently used in emotional branding that their effect on consumers' emotional reactions is either not statistically significant or even negative.

Among the three emotions found to be contagious in B2C context, anger and surprise are of high arousal while sadness is of low arousal which indicates that either high or low arousal emotions can be contagious. The t-tests do not enable us to compare between sadness, anger and surprise to evaluate whether or not high arousal emotions are more contagious than low arousal emotions, we used a one-way ANOVA model to evaluate which of sadness (low arousal), anger (high arousal) or surprise (high arousal) is the most contagious. The three corresponding groups of single emotion brand posts were retained for the ANOVA model. The Emotional Convergence (EC), indicative of B2C emotional contagion, achieved by each brand post is used as the dependent variable and consists of the proportion of emotional reactions matching the brand post's emotion. The one-way ANOVA model indicates that B2C Emotional Convergence is significantly different between sadness, anger and surprise ($F(2, 35{,}625)=1{,}350$, $p<0.001$, $SS=51.70$, $MS=25.83$). Tukey's post-hoc test was used to perform pair-wise comparisons. B2C Emotional Convergence were significantly different across all pairs of emotions among sadness, anger and surprise ($p<0.05$ at Tukey's post-hoc test for each pairwise comparison). The findings also suggest that surprise is more contagious than both sadness and anger, while sadness is the least contagious. Given than sadness is a low arousal emotion and both anger and surprise are high arousal emotions, the findings suggest that high arousal emotions are more contagious than low arousal emotions. These findings confirm prior research (Berger and Milkman, 2012) which suggested that high arousal emotions are more contagious, except for the emotion of love.

Combined effect of multiple emotions in brand posts

While the analysis conducted in the previous section focused on the contagion of single emotions conveyed in brand posts, it is also important to consider the combined effect of multiple emotions on contagion. Indeed, descriptive statistics show that 54.6% of all brand posts include two or more emotions. *Table 9* illustrates the distribution of combined emotions in brand posts. The results indicate that all possible combinations of two emotions are found to co-exist in the brand posts gathered for this study. The combination of love and happiness is the most frequent (22.34% of the posts), followed by happiness and sadness (19%), love and sadness (16.57%), and anger and happiness (11.68%).

Table 9. Descriptive statistics of combination emotions in brand posts

	Love			
Happiness	70,911 (22.34%)	**Happiness**		
Sadness	52,578 (16.57%)	60,300 (19.00%)	**Sadness**	
Anger	34,224 (10.78%)	37,064 (11.68%)	31,339 (9.87%)	**Anger**
Surprise	27,556 (8.68%)	32,893 (10.36%)	27,400 (8.63%)	19,264 (6.07%)

Conveying combined emotions in brand posts, especially emotions of opposite or same valence, raises interesting questions about potential combined effects on B2C emotional contagion. As the emotions of sadness, anger and surprise are found to be contagious from brands to consumers, it would be interesting to examine whether their combination with other emotions would intensify or weaken their contagion effects. To do so, three one-way ANOVA models are performed. The first ANOVA model aims to test whether brand posts that contain surprise mixed with another emotion E would intensify or attenuate the likelihood of consumer emotional reaction of surprise compared to brand posts conveying the single emotion of surprise. To do that, several groups of brand posts conveying surprise and another emotion are formed including brand posts conveying surprise and love, surprise and happiness, surprise and sadness, surprise and anger and those conveying surprise only. The second ANOVA model aims to test whether brand posts that contain anger mixed with another emotion E would intensify or attenuate the likelihood of consumer emotional reaction of anger compared to brand posts conveying the single emotion of anger. To do that, a comparison of brand posts conveying anger and love, anger and happiness, anger and sadness, anger and surprise and those conveying surprise only was conducted. Finally, the third ANOVA model aims to test whether brand posts that contain sadness mixed with another emotion E would intensify or attenuate the likelihood of consumer emotional reaction of sadness compared to brand posts conveying the single emotion of sadness. To do that, a comparison of brand posts conveying sadness and love, sadness and happiness, sadness and anger, sadness and surprise and those conveying sadness only was conducted.

Overall, twelve groups of brand posts are formed including brand posts conveying sadness only (N=18,689), anger only (N=11,550), surprise only (N=8,022), sadness and love (N=52,578), sadness and happiness (N=60,300), sadness and anger (N=31,339), sadness and surprise (N=27,400), anger and love (N=34,224), anger and happiness (N=37,064), anger and surprise (N=19,264), surprise and love (N=27,556) and surprise and happiness (N=32,893). All groups are then combined into three datasets for each ANOVA model accordingly. The Emotional Convergence (EC), indicative of B2C emotional contagion of the emotion of focus in each ANOVA model is used as the dependent variable and consists of the proportion of emotional reactions matching the love, anger or surprise, respectively.

All three ANOVA models are statistically significant, as summarized in *Table 10*, revealing that the combined effect of multiple emotions in brand posts exists and has a statistically significant effect on emotional contagion from brands to consumers (B2C). Tukey's post-hoc tests were also used to perform pair-wise comparisons.

Table 10. Results of ANOVA models testing the difference in B2C Emotional Convergence across combined and single emotions

First ANOVA model: Contagiousness of sadness in mixed emotions F(4, 53,257)= 11.4, p<0.001, SS=0.6, MS=0.157				
Tukey's post-hoc tests for pairwise comparisons of B2C Emotional Convergence	difference	lower	upper	p-value
Sadness + Love vs. Sadness only	0.001	-0.003	0.005	0.992
Sadness + Happiness vs. Sadness only	0.000	-0.004	0.003	1.000
Sadness + Anger vs. Sadness only	0.009	0.004	0.013	0.000
Sadness + Surprise vs. Sadness only	0.009	0.004	0.013	0.000
Second ANOVA model: Contagiousness of anger in mixed emotions F(4, 35,250)= 4.191, p=0.00217, SS=0.3, MS=0.080				
Pairwise comparisons of B2C Emotional Convergence	difference	lower	upper	p-value
Anger + Love vs. Anger only	0.003	-0.003	0.009	0.585
Anger + Happiness vs. Anger only	0.003	-0.003	0.008	0.652
Anger + Sadness vs. Anger only	0.000	-0.007	0.006	1.000
Anger + Surprise vs. Anger only	0.011	0.003	0.019	0.001
Third ANOVA model: Contagiousness of surprise in mixed emotions F(4, 25935)= 5851, p<0.001, SS=1,833, MS=458.3				
Pairwise comparisons of B2C Emotional Convergence	difference	lower	upper	p-value

Surprise + Love vs. Surprise	0.568	0.553	0.582	0.000	✅
Surprise + Happiness vs. Surprise	0.611	0.599	0.624	0.000	✅
Surprise + Sadness vs. Surprise	0.579	0.564	0.593	0.000	✅
Surprise + Sadness vs. Surprise	0.558	0.541	0.574	0.000	✅

✅ = significant, ⛔ = not significant

The findings provide evidence of a combined effects of multiple emotions conveyed at once in brand posts. Such effect is found to be statistically significant for sadness, anger and surprise when combined with one another but also when surprise is combined with any of the other emotions including love, happiness, sadness and anger. First, the contagiousness of sadness is found to be stronger when combined with either anger or surprise, which shows that, when a contagious low arousal emotion is combined with a contagious high arousal emotion, its contagiousness is intensified. Second, the contagiousness of anger is found to be stronger when combined with surprise, which indicates that, when a contagious high arousal emotion is combined with another contagious high arousal emotion, its contagiousness is intensified too. This illustrates a cumulative contagion effect of high arousal emotions. Finally, the contagiousness of surprise is intensified when combined with either love, happiness, sadness or anger. This indicates that surprise, already found to be the most contagious emotion from brands to consumers, is even more contagious whether combined with positive or negative emotions.

Discussion

Analysis of 317,357 brand posts and 83,310,772 consumers' emotional reactions to the brand posts sheds light on which emotions are contagious from brands to consumers, whether the valence and arousal of emotions determine their contagiousness, and how multiple emotions can have a combined effect to amplify or attenuate emotional contagion on Facebook brand pages. Contributing to the debate on whether emotional contagion occurs only between individuals or can extend to consumer-brand interactions through emotional branding, our results demonstrate that emotional contagion occurs indeed between brands and consumers. Our findings also suggest that sadness, anger and surprise are contagious from brands to consumers. Valid for brand posts conveying a single emotion, a comparison of the contagiousness of sadness, anger and surprise revealed that high arousal emotions (surprise and anger) are more contagious than low arousal ones (sadness).

More broadly, our findings demonstrate that the combination of several emotions in brand content contributes to amplify their emotional contagion. The results show that combining a positive emotion (love or happiness) with a negative one (sadness or anger) in brand content does not have a statistically significant effect on the contagiousness of the negative emotion. Marketers wanting to attenuate the contagion effect of negative brand posts can instead focus on webcare interventions and other means of customer care to deal with negative emotional reactions from their consumers rather than combining negative and positive emotions in their brand posts. Nevertheless, the surprise factor of brand posts has been found to be the most contagious and combining surprise with any other emotion is found to have a combined effect that contributes to intensify the contagiousness of surprise itself. Marketers can leverage on these field results by incorporating the emotion of surprise in a wide variety of emotional content for achieving higher emotional contagion.

Nevertheless, the results of study 1 stop short at providing the insights needed to further understand the emotional dynamics beyond the control of the brand in the C2C interactions that unfold in the aftermath of emotional branding. Study 2 addresses those shortcoming by further investigating C2C emotional contagion.

STUDY 2: C2C EMOTIONAL CONTAGION

The objective of study 2 is to examine whether emotional contagion occurs among consumers in consumer-to-consumer (C2C) conversations on Facebook brand pages. In other words, this study looks at whether emotional content conveyed in consumer comments influences other consumers' emotional responses as conveyed in their replies to other consumers' comments. In addition, study 2 helps identify which emotions are contagious from consumer-to-consumer and whether they differ from those emotions that are contagious from brand-to-consumers.

Data

The data used in this study consists of conversational data among consumers in the form of comments and replies to comments on Facebook brand pages. Consumers' comments and their associated consumers' replies were collected using Facebook Graph API resulting in 41,158,070 consumer comments and 14,482,369 consumer replies to comments. Consumers' comments and also replies to comments were subjected to two of the three emotion classification methods described in study 1 including: (1) Unicode character analysis to identify emoticons associated with specific emotions used by the consumers, and (2) Machine Learning based emotion classification of text resulting in a combined outcome as Boolean values (true/false) among a set of five emotions: love, happiness, anger, sadness and surprise.

Results and hypothesis testing

Descriptive statistics

The results of the emotion classification of all collected consumer comments (N=41,158,070) and replies to comments (N=14,482,369) show that the proportion of comments expressing emotions and the proportion of replies expressing emotions are very similar (74.06% and 78.28%). Descriptive statistics of emotional comments and replies to comments are summarized in *Table 11* and *Table 12* and show that love and happiness are the most common emotions expressed in consumer conversations (either comments or replies to comments), followed by sadness, anger and surprise.

Table 11. Classification of emotions in consumer comments

Emotional consumer comments	Love	Happiness	Sadness	Anger	Surprise
Single emotion	4,213,706	5,190,075	2,436,563	1,256,493	821,114
Proportion single emotion	0.102	0.126	0.059	0.031	0.020
Mixed emotions	11,867,881	11,391,108	8,828,921	5,066,310	4,257,630
Proportion mixed emotion	0.288	0.277	0.215	0.123	0.103
Total detected	16,081,587	16,581,183	11,265,484	6,322,803	5,078,744
Proportion Total	0.391	0.403	0.274	0.154	0.123
Detected using emoticons	1,244,153	1,752,199	731,415	91,942	46,341
Detected using text analysis (Machine learning)	15,240,106	15,542,264	10,767,167	6,248,437	5,041,723

Table 12. Classification of emotions in consumer replies to comments

Emotional consumer replies to comments	Love	Happiness	Sadness	Anger	Surprise
Single emotion	1,282,138	1,984,746	714,143	355,191	266,097
Proportion single emotion	0.089	0.137	0.049	0.025	0.018
Mixed emotions	5,047,379	4,819,713	3,475,628	2,214,538	1,848,460
Proportion mixed emotion	0.349	0.333	0.240	0.153	0.128
Total detected	6,329,517	6,804,459	4,189,771	2,569,729	2,114,557
Proportion Total	0.437	0.470	0.289	0.177	0.146
Detected using emoticons	643,031	1,466,045	461,596	38,204	29,147
Detected using text analysis (Machine learning)	5,856,325	5,893,404	3,851,182	2,537,820	2,090,757

C2C emotional contagion

C2C emotional contagion among consumers occurs when a reply to a comment expresses the same emotion as the comment itself, thus achieving a higher Emotional Convergence between the comment and its replies. We start by considering replies to the consumer comments that express a single emotion. Five groups of replies are formed: 1,358,233 replies to love comments, 1,642,518 replies to happy comments, 792,997 replies to sad comments, 426,278 replies to angry comments, and 325,388 replies to surprise comments. The results described in *Table 13* show that comments expressing love or happiness generate the highest emotional convergence (proportion of replies of the same emotion) with 44.6% for love and 50.2% for happiness, compared to sadness (30.1%), anger (21.7%) and surprise (17.8%). Yet, these results do not provide evidence of emotional contagion and further statistical tests are required to demonstrate the contagion effect of specific emotions. To achieve that goal, replies to non-emotional consumer comments (comments that do not convey any emotion at all) are used as a reference group comprising 11,810,960 replies. A bootstrap t-test is conducted using the approach described in Efron and Tibshirani (1993). 5,000 bootstrap samples were used in accordance with the recommendation of Efron (1987). If an emotion E conveyed in consumer comments is contagious, we expect a higher proportion of replies expressing the same emotion E compared to replies to consumer comments not conveying any emotion at all.

The results of the five bootstrap t-tests are reported in *Table 13* along with descriptive statistics for each comparison. The results reveal that all five bootstrap t-tests are significant ($p<0.001$) indicating a statistically significant difference between each group among replies to love, happiness, sadness, anger and surprise and the reference group of replies to non-emotional comments. These results provide evidence of contagiousness of all emotions under investigation from consumer-to-consumer (C2C). These findings are different from the findings of study 1 where only certain emotions were found to be contagious from brand-to-consumers. The fact that every emotion is found to be contagious from consumer-to-consumer explains that consumers are more susceptible of emotional contagion among each other than from brand-to-consumers. One possible explanation to this finding could be that consumers tend distrust emotional brand content compared to consumers' emotional content. Indeed, consumers would perceive brand’s emotion-eliciting strategies as inauthentic and designed as “manipulative persuasion tactics” (Akpinar and Berger, 2017, p.319) to influence on consumers and induce reactance (Campbell and Kiirmani, 2000). From this perspective, brands may not be considered as credible and trustworthy sources because emotions displayed by the brand may be perceived by consumers as not sincere and inauthentic compared to those expressed by other consumers with whom they are interacting.

Table 13. Bootstrap t-tests assessing the emotional contagion from consumer-to-consumer

Group (replies to consumer comments with a single emotion)	**Love**	**Happiness**	**Sadness**	**Anger**	**Surprise**
C2C Emotional Contagion (EC) Mean proportion of consumers' emotional replies expressing the same emotion as the consumer comment	0.447	0.502	0.301	0.217	0.178
Reference sample Mean proportion of consumers' emotional replies expressing the same emotion in response to consumer comments conveying no emotions	0.441	0.475	0.294	0.183	0.150
Difference against the reference sample	0.005 (+1.22%)	0.028 (+5.82%)	0.008 (+2.59%)	0.034 (+18.48%)	0.028 (+18.41%)
Bootstrap t-tests results (based on 5,000 resampling)	**Love vs. No emotion**	**Happiness vs. No emotion**	**Sadness vs. No emotion**	**Anger vs. No emotion**	**Surprise vs. No emotion**
p-value	<0.001 ✅	<0.001 ✅	<0.001 ✅	<0.001 ✅	<0.001 ✅
t statistic	11.946	66.317	14.309	40.922	52.632

✅ = significant, ⛔ = not significant

Combined emotions in consumer content

While the contagiousness of combined emotions and their interaction effects have been reported in Study 1 using brand posts as the vehicle of emotions, a similar analysis is conducted using consumer comments and their effect on the emotional response in consumer replies to other consumer comments. The results produce similar insights and yielded the same conclusions. Table 14 illustrates the distribution of combined emotions in consumer comments. The results indicate that, similar to brand posts, all possible combinations of two emotions are found to co-exist in the consumer comments collected for this study. The combination of love and happiness is the most frequent (in 19.51% of the comments), followed by love and sadness (13.40%) and happiness & sadness (12.63%).

Table 14. Descriptive statistics of combined emotions in consumer comments

	Love			
Happiness	8,033,493 (19.51%)	**Happiness**		
Sadness	5,514,553 (13.40%)	5,197,056 (12.63%)	**Sadness**	
Anger	2,918,193 (7.09%)	2,695,747 (6.55%)	2,486,010 (6.04%)	**Anger**
Surprise	2,389,721 (5.81%)	2,378,672 (5.78%)	2,174,038 (5.28%)	1,455,770 (3.54%)

For each emotion found to be contagious from consumer-to-consumer (love, happiness, sadness, anger and surprise), their combination with each other is expected to intensify or attenuate their contagion effects. Five one-way ANOVA models are performed to test such combined effects, each model focusing on the combination of a given emotion with each of the other emotions. Overall, 15 groups of consumer replies to comments were formed including those replying to love only, happiness only, sadness only, anger only, surprise only, and any combination of two of these emotions. *Table 15* describes the groups of replies used for the ANOVA models.

Table 15. Data sets for the ANOVA models

		ANOVA models				
Groups of replies to comments	**N**	**Love**	**Happiness**	**Sadness**	**Anger**	**Surprise**
Love only	1,358,233	×				
Happiness only	1,642,518		×			
Sadness only	792,997			×		
Anger only	426,278				×	
Surprise only	325,388					×
Love & Happiness	1,377,407	×	×			
Love & Sadness	653,878	×		×		
Love & Anger	322,367	×			×	
Love & Surprise	234,170	×				×
Happiness & Sadness	529,183		×	×		
Happiness & Anger	274,256		×		×	
Happiness & Surprise	216,885		×			×
Sadness & Anger	234,468			×	×	
Sadness & Surprise	159,066			×		×
Anger & Surprise	108,501				×	×

The groups are combined into five datasets for each ANOVA model as illustrated in *Table 15*. The Emotional Convergence (EC), indicative of C2C emotional contagion of the emotion of focus in each ANOVA model is used as the dependent variable. It consists of the proportion of replies expressing the emotion of focus in each ANOVA model.

All five ANOVA models are statistically significant, as summarized in *Table 16*, indicating that the combined effect of multiple emotions in consumer comments exists and has a statistically significant effect on emotional contagion from consumer-to-consumer. Tukey’s post-hoc tests were also used to perform pair-wise comparisons. A large majority of Tukey’s post-hoc tests were significant and indicates how each pair of emotions impact the contagion effect of each other. Key highlights from the results in *Table 16* include a significant interaction between love and happiness in C2C emotional contagion. When combined with love, happiness helps boost the contagion effect of love. However, this combination would also result in a reduction of the contagion effect of happiness itself. This seems to indicate that happiness supports the contagion effect of love to the detriment of its own contagion effect.

When combined with any other emotion, love gets more contagious. This indicates that, not only love is a strong emotion in terms of contagiousness in C2C interactions, but also that other emotions, either positive of negative, help strengthen the contagiousness of love. For example, the highest difference of mean in contagiousness of love was found between replies to consumer comments expressing love only and replies to consumer comments expressing both love and sadness. As such, love is an emotion that can be used by consumers in both positive and negative situations and its contagion effect remains strong.

Sadness is found to be less contagious when combined with happiness. This supports the idea that positive emotions tend to attenuate the effect of negative ones. The opposite is also found to be significant. Indeed, happiness is found to be less contagious too when combined with sadness. This indicates a mutual attenuation of contagiousness for positive and negative emotions like happiness and sadness. However, the contagion effect of sadness is found to be stronger when combined with either anger, surprise or love, all of which being high arousal emotions. This indicates that when combined with a negative emotion like sadness, high arousal emotions boost its contagion effect.

In contrast to the ambivalence of love indicated by its stronger contagion effect when combined with any emotion, the contagion effect of anger is found to be weaker when combined with happiness while happiness gets more contagious when combined with anger. This indicates that, despite being low in arousal, positive emotions can attenuate high arousing negative emotions. Finally, any emotion (except sadness) gets more contagious when combined with surprise, supporting the idea of a surprise effect in C2C emotional contagion. However, its strongest effect is when it is combined with anger. In fact, both surprise and anger are more contagious when combined together in consumer comments. This indicates a mutual amplification of contagiousness for anger and surprise in C2C interactions.

Table 16. Results of ANOVA models testing the difference in C2C Emotional Convergence across combined and single emotions

First ANOVA model: Contagiousness of **love** in mixed emotions
F(4, 1,832,680)=147.5, SS=114, MS=28.4, p<0.001 ✅

Pairwise comparisons of C2C EC	difference	lower	upper	p-value
Love + Happiness vs. Love only	0.003	0.001	0.005	0.001 ✅
Love + Sadness vs. Love only	0.023	0.020	0.025	0.000 ✅
Love + Anger vs. Love only	0.005	0.002	0.009	0.001 ✅
Love + Surprise vs. Love only	0.007	0.003	0.011	0.000 ✅

Second ANOVA model: Contagiousness of **happiness** in mixed emotions
F(4, 2,009,923)=253.5, SS=201, MS=50.3, p<0.001 ✅

Pairwise comparisons of C2C EC	difference	lower	upper	p-value
Happiness + Love vs. Happiness only	-0.008	-0.010	-0.006	0.000 ✅
Happiness + Sadness vs. Happiness only	-0.026	-0.029	-0.024	0.000 ✅
Happiness + Anger vs. Happiness only	0.011	0.007	0.015	0.000 ✅
Happiness + Surprise vs. Happiness only	0.010	0.006	0.014	0.000 ✅

Third ANOVA model: Contagiousness of **sadness** in mixed emotions
F(4, 1,110,707)=194.4, SS=124, MS=30.9, p<0.001 ✅

Pairwise comparisons of C2C EC	difference	lower	upper	p-value
Sadness + Love vs. Sadness only	0.021	0.019	0.024	0.000 ✅
Sadness + Happiness vs. Sadness only	-0.006	-0.009	-0.003	0.000 ✅
Sadness + Anger vs. Sadness only	0.010	0.006	0.014	0.000 ✅
Sadness + Surprise vs. Sadness only	0.004	-0.001	0.008	0.196 ⛔

Fourth ANOVA model: Contagiousness of **anger** in mixed emotions
F(4, 534,678)=75.0, SS=30, MS=7.5, p<0.001 ✅

Pairwise comparisons of C2C EC	difference	lower	upper	p-value
Anger + Love vs. Anger only	0.009	0.006	0.013	0.000 ✅
Anger + Happiness vs. Anger only	-0.009	-0.013	-0.006	0.000 ✅
Anger + Sadness vs. Anger only	0.003	0.000	0.007	0.091 ⛔
Anger + Surprise vs. Anger only	0.017	0.012	0.022	0.000 ✅

Fifth ANOVA model: Contagiousness of **surprise** in mixed emotions
F(4, 416,962)=25.4, SS=9, MS=2.3, p<0.001 ✅

Pairwise comparisons of C2C EC	difference	lower	upper	p-value
Surprise + Love vs. Surprise only	0.005	0.002	0.009	0.000 ✅
Surprise + Happiness vs. Surprise only	-0.002	-0.006	0.001	0.459 ⛔
Surprise + Sadness vs. Surprise only	0.009	0.005	0.013	0.000 ✅
Surprise + Anger vs. Surprise only	0.012	0.007	0.017	0.000 ✅

✅= significant, ⛔ = not significant

Discussion

Analysis of 41,158,070 consumer comments and 14,482,369 consumer replies to comments sheds light on the dynamics of emotional contagion from consumer-to-consumer and how the results compare to the emotional contagion from brands to consumers. The empirical results reinforce the findings from study 1 that anger and surprise are among the most contagious emotions on Facebook brand pages either from B2C or C2C. The results also provide insights into how combined emotions impact their contagion effects in C2C conversations. In particular, positive emotions are found to attenuate negative ones. Love is found to be used by consumers in an ambivalent way, combined with either other positive or negative emotions, yet retaining and even amplifying its contagion effect. The contagious effect of anger was found to be attenuated when combined with happiness. These insights can help marketers to increase the potential of their emotional branding efforts by leveraging on these field results to create the ideal configuration of valence and arousal for achieving higher emotional contagion by incorporating the right emotional combinations into brand emotional content that would yield to the right emotional combinations in consumer conversations.

GENERAL DISCUSSION AND MANAGERIAL IMPLICATIONS

Marketing practitioners have become increasingly interested in emotional branding strategies as an effective means to establish a strong emotionally evocative relationship with consumers. However, while there is a consensus on the benefits of emotional branding (Gobé 2001; Atkin 2004; Roberts 2004; Lindstrom 2005), not much is known about the mechanisms that enable brands to put into practice these strategies. Understanding how emotional contagion operates on Facebook brand pages is crucial for marketers to design and implement successful emotional branding strategies.

The results of two studies, supported by large field data from Facebook brand pages, demonstrate that emotional contagion occurs from brands to consumers as well as among consumers. The results come as call for caution due to the stronger contagion effect of negative emotions such as anger and sadness, but they also come as a set of insights into how emotions can be combined in a way that would amplify the contagion effect of certain emotions while weakening the contagion effect of other emotions. On Facebook brand pages, consumers engage with the brand and also with other consumers. Understanding how emotions combine and affect each other's contagion effects sheds light on interesting ways to improve the spread of certain emotions. An interesting finding in this paper is the strong role of the emotion surprise in strengthening the emotional contagion of other emotions. This finding is consistent with the work of Berger and Milkman (2012) and Tucker (2015), who found that surprising content is more likely to be passed on. Anger also has been found to boost contagion among individuals (Berger, 2011; Berger and Milkman, 2012) and the findings in this paper corroborate that.

While prior research (Berger and Milkman, 2012; Akpinar and Berger, 2017) has investigated why emotional content is more likely to be shared, this paper examines whether and how online emotional content is transmitted on social media. A main contribution of this paper is to examine the contagiousness of consumer-emotional generated content, which is of a great interest for marketers who "encourage consumer-generated content in the hope that people will share this content with others" (Berger and Milkman, 2012, p.192) to increase its exposure to a broader audience. Understanding how consumers engage emotionally with one another, allows marketers to design and implement effective emotional branding strategies appealing to consumers' emotions on Facebook brand pages. This would help brand marketers to create the right configuration of emotions in their emotional branding strategies.

LIMITATIONS AND FURTHER RESEARCH

Like any research, this work has its limitations which serve as avenues for further research. First, we used a sample of "most talked about" Facebook brand pages. Instead, sampling could be done within specific industry categories in which emotional branding is prevalent such as non-profit organizations, luxury brands, fashion industry, etc. Second, further analysis of the interaction effect of brand replies to consumers' comments would fill the gap in the literature as pointed out by Gotthilf (2010) who claim that brands should leverage the two-way conversations enabled by social media platforms. Examining the effect of brand interventions in consumer-to-consumer conversations at the emotional level would help to further our understanding of emotional dynamics in brand-related social media conversations beyond the emotional branding in brand posts. Another interesting avenue for research is to investigate how highly connected consumers to the brand influence emotional reactions of on other consumers, and examine the emotional arguments or persuasive cues in consumers' emotional content used to influence other consumers and attenuate the negative emotional contagion in online consumer-to-consumer conversations.

In the new era of AI enabled digital assistants and chatbots, it would be interesting to explore how brands can leverage such new technologies to engage emotionally with consumers. To what extent can chatbots connect with consumers on emotional level? Will chatbots help brands to combat negative emotional contagion? What are the ethical considerations of such a practice? To extend the present work, a fruitful avenue for future research would be to take a closer look at the ethical use of artificial intelligence in designing and using emotionally intelligent chatbots capable of connecting emotionally with online brand communities and the issues that could arise in light of this technological progress. Future research should also examine the impact of online emotional states on offline emotional states of consumers and therefore their offline behavior in terms of product purchase. One avenue for future research would be to examine the temporal dimension of emotional contagion on social media in terms of its durability or its persistence over time. Emotional ambivalence could also be explored using a longitudinal analysis to investigate the change of emotional state of the same consumers experiencing ambivalent emotions over time and its impact on emotional contagion within online brand community.

REFERENCES

Adelmann, P. K., & Zajonc, R. B. (1989). Facial efference and the experience of emotion. *Annual review of psychology*, *40*(1), 249-280.

Akpinar, E., & Berger, J. (2017). Valuable virality. *Journal of Marketing Research*, *54*(2), 318-330.

Algesheimer, R., Dholakia, U. M., & Herrmann, A. (2005). The social influence of brand community: Evidence from European car clubs. *Journal of marketing*, *69*(3), 19-34.

Atkin, D. (2004). *The culting of brands: When customers become true believers*. Portfolio (Hardcover).

Bagozzi, R. P., Gopinath, M., & Nyer, P. U. (1999). The role of emotions in marketing. *Journal of the academy of marketing science*, *27*(2), 184-206.

Barrett, L. F., & Russell, J. A. (1998). Independence and bipolarity in the structure of current affect. *Journal of personality and social psychology*, *74*(4), 967.

Barsade, S. G. (2002). The ripple effect: Emotional contagion and its influence on group behavior. *Administrative Science Quarterly*, *47*(4), 644-675.

Batra, R., Ahuvia, A., & Bagozzi, R. P. (2012). Brand love. *Journal of marketing*, *76*(2), 1-16.

Baumeister, R. F., Bratslavsky, E., Finkenauer, C., & Vohs, K. D. (2001). Bad is stronger than good. *Review of general psychology*, *5*(4), 323.

Berger, J., & Milkman, K. L. (2012). What makes online content viral?. *Journal of marketing research*, *49*(2), 192-205.

Burgoon, J. K., Magnenat-Thalmann, N., Pantic, M., & Vinciarelli, A. (Eds.). (2017). Social signal processing. *Cambridge University Press*.

Campbell, M. C., & Kirmani, A. (2000). Consumers' use of persuasion knowledge: The effects of accessibility and cognitive capacity on perceptions of an influence agent. *Journal of consumer research*, *27*(1), 69-83.

Chartrand, T. L., & Bargh, J. A. (1999). The chameleon effect: the perception–behavior link and social interaction. *Journal of personality and social psychology*, *76*(6), 893.

Chen, T., & Guestrin, C. (2016, August). Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining* (pp. 785-794). ACM.

Cheshin, A., Rafaeli, A., & Bos, N. (2011). Anger and happiness in virtual teams: Emotional influences of text and behavior on others' affect in the absence of non-verbal cues. *Organizational Behavior and Human Decision Processes*, *116*(1), 2-16.

Cialdini, R. B., & Kenrick, D. T. (1976). Altruism as hedonism: a social development perspective on the relationship of negative mood state and helping. *Journal of personality and social psychology*, 34(5), 907.

Collins, N. L., & Miller, L. C. (1994). Self-disclosure and liking: a meta-analytic review. *Psychological bulletin*, *116*(3), 457.

Coviello, L., Sohn, Y., Kramer, A. D., Marlow, C., Franceschetti, M., Christakis, N. A., & Fowler, J. H. (2014). Detecting emotional contagion in massive social networks. *PloS one*, *9*(3), e90315.

Dessart, L., Veloutsou, C., & Morgan-Thomas, A. (2016). Capturing consumer engagement: duality, dimensionality and measurement. *Journal of Marketing Management*, *32*(5-6), 399-426.

Dimberg, U. (1982). Facial reactions to facial expressions. *Psychophysiology*, *19*(6), 643-647.

Efron, B. (1987). Better bootstrap confidence intervals. *Journal of the American statistical Association*, 82(397), 171-185.

Efron, B., & Tibshirani, R. J. (1993). The jackknife. In An introduction to the bootstrap (pp. 141-152). Springer US.

Ekman, P., & Friesen, W. V. (1971). Constants across cultures in the face and emotion. *Journal of personality and social psychology*, *17*(2), 124.

Ekman, P., Friesen, W. V., & Hager, J. (2002). *Emotional facial action coding system. Manual and investigator's guide CD-ROM. Salt Lake City: A Human Face*.

Ekman, P., Friesen, W. V., & Scherer, K. R. (1976). Body movement and voice pitch in deceptive interaction. *Semiotica*, *16*(1), 23-28.

Ellemers, N., Kortekaas, P., & Ouwerkerk, J. W. (1999). Self-categorization, commitment to the group and social self-esteem as related but distinct aspects of social identity.

Evans, V. (2017). *The Emoji Code: How Smiley Faces, Love Hearts and Thumbs Up are Changing the Way We Communicate*. Michael O'Mara Books.

Ferrara, E., & Yang, Z. (2015). Measuring emotional contagion in social media. *PloS one*, 10(11), e0142390.

Fiske, S. T. (1980). Attention and weight in person perception: The impact of negative and extreme behavior. *Journal of personality and Social Psychology, 38*(6), 889.

Fournier, S. (1998). Consumers and their brands: Developing relationship theory in consumer research. *Journal of consumer research*, *24*(4), 343-373.

Fowler, J. H., & Christakis, N. A. (2008). Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham Heart Study. *Bmj*, *337*, a2338.

Friedman, H. S., Prince, L. M., Riggio, R. E., & DiMatteo, M. R. (1980). Understanding and assessing nonverbal expressiveness: The affective communication test. *Journal of personality and social psychology*, *39*(2), 333.

Fussell, S. R. (Ed.). (2002). *The verbal communication of emotions: interdisciplinary perspectives*. Psychology Press.

Gobé, M. (2001). *Emotional branding: the new paradigm for connecting brands to people*. New York. Allworth Press.

Gottman, J. M., & Levenson, R. W. (1986). Assessing the role of emotion in marriage. *Behavioral Assessment*.

Gotthilf, G., 2010. *7 practical steps to managing a Facebook crisis*. Blueglass, September 30, available at: www.blueglass.com/blog/7-practical-steps-to-managing-a-facebook-crisis/

Gummerus, J., Liljander, V., Weman, E., & Pihlström, M. (2012). Customer engagement in a Facebook brand community. *Management Research Review*, *35*(9), 857-877.

Hatfield E., Cacioppo, J., & Rapson, R. L. (1994). Emotional contagion. New York, Cambridge University Press.

Hollebeek, L. D., Glynn, M. S., & Brodie, R. J. (2014). Consumer brand engagement in social media: Conceptualization, scale development and validation. *Journal of interactive marketing*, *28*(2), 149-165.

Ito, T. A., Larsen, J. T., Smith, N. K., & Cacioppo, J. T. (1998). Negative information weighs more heavily on the brain: The negativity bias in evaluative categorizations. *Journal of personality and social psychology*, *75*(4), 887.

Izard, C. E. (2013). *Patterns of emotions: A new analysis of anxiety and depression*. Academic Press.

Jaakkola, E., & Alexander, M. (2014). The role of customer engagement behavior in value co-creation: a service system perspective. *Journal of Service Research*, *17*(3), 247-261.

Kiritchenko, S., Zhu, X. and Mohammad, S.M. (2014). "Sentiment analysis of short informal texts", *Journal of Artificial Intelligence Research*, Vol. 50, pp. 723-762.

Kramer, A. D., Guillory, J. E., & Hancock, J. T. (2014). Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences*, *111*(24), 8788-8790.

Kwak, H., Lee, C., Park, H., & Moon, S. (2010, April). What is Twitter, a social network or a news media?. In *Proceedings of the 19th international conference on World wide web* (pp. 591-600). ACM.

Levenson, R. W., & Gottman, J. M. (1985). Physiological and affective predictors of change in relationship satisfaction. *Journal of personality and social psychology*, 49(1), 85.

Lindstrom, M. (2005). Broad sensory branding. *Journal of Product & Brand Management*, *14*(2), 84-87.

Lohmann, K., Pyka, S. S., & Zanger, C. (2017). The effects of smileys on receivers' emotions. *Journal of Consumer Marketing*, *34*(6), 489-495.

Lundqvist, L. O., & Dimberg, U. (1995). Facial expressions are contagious. *Journal of Psychophysiology*.

Lynch, J., & De Chernatony, L. (2004). The power of emotion: Brand communication in business-to-business markets. *Journal of Brand management*, *11*(5), 403-419.

Marzocchi, G., Morandin, G., & Bergami, M. (2013). Brand communities: loyal to the community or the brand?. *European Journal of Marketing*, *47*(1/2), 93-114.

Mitchell, M., Brown, K., Morris-Villagran, M., & Villagran, P. (2001). The effects of anger, sadness and happiness on persuasive message processing: A test of the negative state relief model. *Communication Monographs*, *68*(4), 347-359.

Morrison, S., & Crane, F. G. (2007). Building the service brand by creating and managing an emotional brand experience. *Journal of Brand Management*, *14*(5), 410-421.

Park, J., Chung, H., & Rutherford, B. (2011). Social perspectives of e-contact center for loyalty building. *Journal of Business Research*, *64*(1), 34-38.

Pratto, F., & John, O. P. (1991). Automatic vigilance: the attention-grabbing power of negative social information. *Journal of personality and social psychology*, *61*(3), 380.

Pugh, S. D. (2001). Service with a smile: Emotional contagion in the service encounter. *Academy of management journal*, 44(5), 1018-1027.

Ren, Y., Kraut, R., & Kiesler, S. (2007). Applying common identity and bond theory to design of online communities. *Organization studies*, *28*(3), 377-408.

Roberts, K. (2004). *Lovemarks: The future beyond brands*. New York: Powerhouse Books.

Robinson, J., & McArthur, L. Z. (1982). Impact of salient vocal qualities on causal attribution for a speaker's behavior. *Journal of personality and social psychology*, *43*(2), 236.

Schivinski, B., Christodoulides, G., & Dabrowski, D. (2016). Measuring consumers' engagement with brand-related social-media content: development and validation of a scale that identifies levels of social-media engagement with brands. *Journal of Advertising Research*, *56*(1), 64-80.

Schoenewolf, G. (1990). Emotional contagion: Behavioral induction in individuals and groups. *Modern Psychoanalysis*.

Skovholt, K., Grønning, A., & Kankaanranta, A. (2014). The communicative functions of emoticons in workplace e-mails: :-). *Journal of Computer-Mediated Communication*, *19*(4), 780-797.

Smith, C. A., & Ellsworth, P. C. (1985). Patterns of cognitive appraisal in emotion. *Journal of personality and social psychology*, *48*(4), 813.

Thompson, C. J., Rindfleisch, A., & Arsel, Z. (2006). Emotional branding and the strategic value of the doppelgänger brand image. *Journal of marketing*, *70*(1), 50-64.

Tsai, H. T., & Bagozzi, R. P. (2014). Contribution behavior in virtual communities: cognitive, emotional, and social influences. *Mis Quarterly*, *38*(1).

van Doorn, J., Lemon, K. N., Mittal, V., Nass, S., Pick, D., Pirner, P., & Verhoef, P. C. (2010). Customer engagement behavior: Theoretical foundations and research directions. *Journal of service research*, *13*(3), 253-266.

van Reijmersdal, E. A., Neijens, P. C., & Smit, E. G. (2007). Effects of television brand placement on brand image. *Psychology & marketing*, *24*(5), 403-420.

Verhoef, P. C., Reinartz, W. J., & Krafft, M. (2010). Customer engagement as a new perspective in customer management. *Journal of service research, 13*(3), 247-252.

Watson, D., & Tellegen, A. (1985). Toward a consensual structure of mood. *Psychological bulletin*, 98(2), 219.

Wojnicki, A., & Godes, D. (2008). Word-of-mouth as self-enhancement. Working paper, University of Toronto.

Conclusion to paper III

The second paper of the thesis contributes to further our understanding of how emotions shape social media interactions in a branding context. The results of two empirical studies, supported by large field data from 942 Facebook brand pages, demonstrate that emotional contagion occurs not only between brands and consumers through emotional branding but also extend to consumer-to-consumer interactions. The results also indicate that negative emotions are more contagious than positive ones, and that high arousal emotions are more contagious than low arousal emotions, in both B2C and C2C interactions. Furthermore, combining emotions in brand content induces an interaction effect capable of intensifying or attenuating their contagion effect.

Understanding how consumers engage emotionally with the brand and with one another helps marketers to design the right configuration of emotions and implement effective emotional branding strategies on Facebook brand pages.

Chapter 5: Thesis Conclusion

Social media have redefined digital marketing in unprecedented ways over the past decade. Consumers are no longer passive recipients of marketing content but rather empowered co-creators and disseminators of brand related content. They form interconnected brand communities, actively engaging with brands and with one another and influencing how branding works in the 21st century. Although this fundamental technological change has provided brand marketers many opportunities to interact with consumers and take advantage of the unfettered consumer data to tune their social media marketing strategies, it also has created several challenges. Indeed, after a bad experience with a brand, unsatisfied consumers often engage in negative word-of-mouth that can create a ripple effect among interconnected brand communities, potentially harming the brand through revengeful comments (e.g. Bechwati and Morrin, 2003), calls for boycotts (e.g. Klein, Smith and John, 2004), or brand sabotage (Kähr et al., 2016). Also, the shift in power from marketers to consumers has challenged brand managers to take control of consumers' online conversations.

Many textbook examples show how consumers, empowered by social media technologies, spread large scale waves of criticism towards brands when wrong business decisions are made, and how such empowerment often ends up influencing brand managers to drop their decisions and follow consumers' demands. For example, Netflix, a streaming and DVD service, faced a strong backlash on social media when it planned to raise its subscription fees by $6 back in 2011 without providing any service upgrades (Gilbert, 2011). Consumers, angry at the decision, engaged in negative word-of-mouth to voice their complaints and disagreement with the brand by massively using the #Netflix hashtag on Twitter, pushing

Netflix executives to drop their decision. Yet, detrimental effects were significant as Netflix lost 800,000 subscribers in the last quarter of that year (Gilbert, 2011). Facing these challenges, brand managers are looking for effective means to engage with consumers on social media and manage their online conversations.

Prior research has advanced our knowledge of consumer brand engagement as consumers' cognitive, emotional and behavioral activities during their interactions with the brand (e.g. Hollebeek, Glynn and Brodie, 2014) as well as with other brand community members (Dessart et al., 2016). However, much of the research is conceptual in nature with little empirical evaluation of social media marketing strategies conducted. This thesis has sought to examine consumer and brand engagement more comprehensively using actual engagement data from Facebook brand pages. Three papers formed this thesis. The first paper investigated the behavioral dimension of engagement by examining the intricacies between consumer engagement and brand engagement behaviors on Facebook brand pages. Because brand engagement has received little attention, the objective of the second paper was to examine empirically the effect of brand interventions in online consumer-to-consumer conversations. The third paper was set out to explore the emotional dynamics between consumers and brands as well as among consumers on Facebook brand pages.

A conceptual model capturing the interplay between brand engagement behaviors and consumer engagement behaviors as well as among consumers themselves was proposed in the first paper. The model was empirically evaluated using more than 525,000 brand posts, 1,706,656 consumer comments and 64,729 brand replies published on 2,740 Facebook brand pages across 25 industries over a twelve month period. Findings shed light on how marketers can design and implement more effective social media marketing strategies. Brand presence and responsiveness to consumer feedback were found to have a positive effect on consumer engagement with the brand and among each other. Furthermore, several characteristics of brand engagement were found to play a significant role in shaping consumer engagement behaviors.

These included the format of brand posts, for which vivid content was found to be most effective, and the promptness of brand replies to consumer comments. Consumers were also found to significantly influence each other, with negative consumer feedback found to have a stronger negative effect on consumer conversations than positive feedback, confirming the empowerment effect of social media on consumers and how such empowerment can manifest itself greatly in negative brand situations.

Brands can intervene in consumer conversations to moderate their emotional reactions. The second paper reported in this thesis examined the impact of 64,347 webcare interventions embedded within 24,557 consumer conversations on Facebook brand Pages to determine the effect of webcare on consumer conversations. While a few studies (van Noort and Willemsen 2012; Schamari and Schaefers 2015) have investigated the effect of webcare interventions on either negative or positive word-of-mouth, it remained unclear how consumers react to webcare interventions with regards to type (proactive versus of reactive), voice (personal versus impersonal), timing (early versus late) and number (single versus multiple). The findings of the second paper, indicated the positive cumulative effect of multiple webcare interventions, the negative effect of reactive webcare interventions compared to proactive ones, the positive effect of personalizing webcare interventions as well as the importance of critical timing of webcare interventions. These findings help brand managers better understand how webcare interventions influence consumer conversations, enabling them to plan and execute adequate webcare strategies when needed.

Drawing on emotional branding and contagion research, findings of the third paper were based on the analysis of 942 Facebook brand pages. This thesis suggests that through emotional contagion, brand marketers can implement effective emotional branding strategies on Facebook brand pages. Very few research (e.g. Kramer, Guillory and Hancock, 2014) have investigated emotional contagion on Facebook. However they were limited to examine the spread of emotions among friends. This thesis provides insights into the phenomenon of emotional contagion applied to a branding context. As such, brand managers benefit greatly from the findings reported in this thesis to design and implement strategies to spread specific emotions conveyed in brand posts among brand communities on Facebook brand pages.

Although the papers provided in this thesis contribute to advance our understanding of online consumer and brand engagement, the results are tailored to one social media platform: Facebook. Generalizing the findings to other platforms such as Twitter, Google+, LinkedIn or Tumblr warrants caution, despite the similarities between Facebook and these platforms. While most Facebook consumer and brand engagement behaviors discussed in this thesis have their equivalent in other social media platforms, they often have different names (e.g. Google's +1 is the equivalent of Facebook's Like) and can potentially have different effects. It is also important to stress that brands tend to use multiple social media platforms at once, posting either the same content on all platforms or tailoring content to each platform. Studying the dynamics of consumer and brand engagement across platforms would reveal further insights as to how to manage disparate consumer conversations, or how emotions spread from one platform to another.

References

Bechwati, N. N., & Morrin, M. (2003). Outraged consumers: Getting even at the expense of getting a good deal. *Journal of Consumer Psychology*, 13(4), 440-453.

Dessart, L., Veloutsou, C., & Morgan-Thomas, A. (2016). Capturing consumer engagement: duality, dimensionality and measurement. *Journal of Marketing Management*, 32(5-6), 399-426.

Gilbert, J.O. (2011, October 24). Netflix account losses much higher than expected after pricing backlash. *The Huflington Post.* Retrieved on February 1st 2018 from: https://www.huffingtonpost.com.au/entry/netflix-account-losses-q3-2011_n_1029269

Hollebeek, L. D., Glynn, M. S., & Brodie, R. J. (2014). Consumer brand engagement in social media: Conceptualization, scale development and validation. *Journal of interactive marketing*, 28(2), 149-165.

Kähr, A., Nyffenegger, B., Krohmer, H., & Hoyer, W. D. (2016). When hostile consumers wreak havoc on your brand: The phenomenon of consumer brand sabotage. *Journal of marketing*, 80(3), 25-41.

Klein, Jill Gabrielle, N. Craig Smith, and Andrew John. (2004), "Why we boycott: Consumer motivations for boycott participation." *Journal of Marketing*, 68, 3 92-109.

Kramer, A. D., Guillory, J. E., & Hancock, J. T. (2014). Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences*, 111(24), 8788-8790.

Schamari, Julia, and Tobias Schaefers. (2015), "Leaving the home turf: how brands can use webcare on consumer-generated platforms to increase positive consumer engagement." J*ournal of Interactive Marketing*, 30 20-33.

van Noort, Guda, and Lotte M. Willemsen. (2012), "Online damage control: The effects of proactive versus reactive webcare interventions in consumer-generated and brand-generated platforms." *Journal of Interactive Marketing*, 26, 3 131-140.

Appendices

Appendix A

Paper presented at the Winter AMA Conference, 2017

Brand interventions and emotional dynamics in online consumer-to-consumer conversations: An empirical investigation

Chedia Dhaoui, Macquarie University, Australia, chedia.dhaoui@mq.edu.au

Cynthia M. Webster, Macquarie University, Australia, cynthia.webster@mq.edu.au

LayPeng Tan, Macquarie University, Australia, laypeng.tan@mq.edu.au

Abstract. Understanding how brand interventions affect the emotional dynamics in consumer to-consumer conversations is an important yet relatively unexplored issue in the study of online consumer brand engagement. To address this concern, we analyze a large dataset from 2,740 Facebook brand pages across 25 industry sectors consisting of 64,347 brand interventions embedded within 24,557 consumer conversations. Our results show that most of the emotional content within consumer conversations is positive prior to brand interventions and that most brands intervene once by proactively adding new, unsolicited comments. Brand interventions affect both positive and negative consumer emotional engagement over time, though the effects are stronger for negative emotional engagement. When brands intervene in negative conversations, they should be proactive but not personalized. Finally, delayed interventions have a stronger effect on reducing negative consumer engagement, as quick interventions are less likely to respond thoroughly to negative consumer comments. These findings provide preliminary evidence to Facebook brand managers in search of effective brand intervention strategies identifying crucial factors to consider in the design, monitoring and management of online consumer conversations surrounding their brands.

Keywords: Consumer-to-consumer conversations; Brand interventions; Emotional dynamics; Facebook brand pages.

Introduction

With the remarkable development of online social networks, brand managers have had to rethink the way they engage with brand communities on social media platforms. Empowered by new communication technologies, consumers are now actively involved in many-to-many communications with brands, as well as with other consumers (Henning- Thurau et al., 2010; Hoffman and Novak, 2011). Instead of merely consuming brand related information (Muntinga, Moorman, and Smit, 2011), consumers these days are able to create and exchange user-generated content (UGC) about brands (Kaplan and Haenlein, 2010). They come together in online communities to share their brand-related thoughts, feelings and emotionally charged comments. Research shows emotional content influences positive and negative word-of-mouth (WOM) communications of other consumers, which in turn, can influence others (Scarduzio & Tracy, 2015) involving multiple people in a cycle of emotional influence (Hareli & Rafaeli, 2008). As such, monitoring and managing consumer emotional engagement in consumer-to-consumer conversations has become a pivotal part of brand management (Schamari and Shaefers, 2015).

Consumer emotional engagement can occur quite quickly as a response to brand posts or reaction to consumer generated content (Baumeister et al. 2007; Moe & Trusov, 2011). Studies find negative consumer emotional engagement to have detrimental effects on brand evaluation, brand choice, purchase behavior and brand loyalty (Chevalier and Mayzlin, 2006; Chiou and Cheng, 2003; Vermeulen and Seegers, 2009) whereas high levels of positive consumer emotional engagement improve attitude and lead to favorable behavior (Brodie et al., 2013; Gummerus et al. 2012; Seraj 2012). Experimental evidence shows individuals, even when have a positive brand experience, are influenced by other consumers' negative online WOM

(Schlosser, 2005). Consequently, brands are in search of effective strategies to intervene in consumer-to-consumer conversations in order to attenuate negative online chatter (Fournier and Avery, 2011) and leverage positive consumer emotional engagement (Hennig-Thurau et al., 2010; Vivek, Beatty and Morgan, 2012).

Facebook brand pages are one type of interactive social platform that facilitate online consumer conversations and enable firms to engage with consumers in a direct and transparent manner (Dellarocas, 2003, 2006). Amid consumer- conversations on Facebook, brands can be a passive or an active actor (Dholakia et al., 2009).or they can take a hybrid approach to interact with consumers and contribute in consumer-to-consumer conversations (Dholakia et al., 2009; Shau, Muniz and Arnauled, 2009). Brands also can engage once with a single intervention or introduce multiple interventions into consumer conversations. In this regard, a brand intervention can be defined as a discrete event generated by the brand during a consumer conversation. For example, brands can intervene by replying to a consumer comment or taking part in the conversation by adding new comments. Consumers can also further respond to brand interventions by posting more comments.

Despite significant practitioner interest, little empirical research examines brand interventions in response to emotional consumer engagement on Facebook brand pages. . Recent work looks at different types of brand intervention strategies, such as proactive versus reactive (van Noort and Willemsen, 2011) and personal versus impersonal (Schamari and Schaefers, 2015). Other studies examine the intensity and quickness of firm engagement in online forums (Homburg, Ehm, & Artz, 2015). Much of this prior research focuses on a single product category or a single firm setting (Goh, Heng, and Lin, 2013; Rishika et al., 2013) or rely on self-reported data which may not reflect actual consumer behavior and hence may limit the external validity of the findings (Geylani, Hofstede, and Inman, 2008).

Based on a large scale dataset of consumer-to-consumer conversations on Facebook brand pages, our study seeks to contribute further insights into the underlying dynamic mechanism of brand interventions and their effects on emotional consumer engagement. This research addresses three managerially relevant questions: 1) To what extent do brand interventions affect emotional consumer engagement in online consumer-to-consumer conversations? 2) What are the most effective brand intervention strategies to improve consumer emotional engagement? and 3) Do timing and frequency of brand interventions have positive or negative reciprocal effects on consumer emotional engagement?

Study results indicate that the effects of brand interventions are stronger on negative consumer emotional engagement and weaker at promoting positive consumer engagement. In most cases brand interventions mitigate the effect of negative consumer comments over time but proactive, non-personalized and delayed brand interventions are more effective than reactive, personalized and quick interventions. Finally, the findings of this research extend the emotional branding literature by examining a large, longitudinal dataset of observed consumer interactions.

Method

Data collection. The initial sampling frame came from the 2015 Inc.5000 annual brand list of the 5000 fastest-growing private companies in the U.S. published by Inc. Magazine. We manually identified brands with an official Facebook brand page. Companies without an official Facebook brand page were excluded from the sample. We further refined the sample and only considered Facebook brand pages that: a) had at least one brand post during 2015, b) had at least 100 fans (likes) and c) allowed data collection via the Facebook Graph API. We then used Facebook Graph API to gather data between 01/01/2015 to 31/12/2015 from the retained 2,740 Facebook brand pages across 25 industry sectors. The final dataset consists of all brand posts and their associated consumer-to-consumer conversations as well as brand interventions in the conversations. In total, there are 107,784 consumer conversation threads, among which 24,557 (22.78%) conversations have brand interventions.

Classifying brand interventions. Brands can intervene into consumer conversations by either reactively replying to specific consumer queries or by proactively adding a new, unsolicited comment to the conversation (van Noort and Willemsen, 2012). We classified brand interventions as either "reactive" for direct replies to explicit consumer queries or "proactive" otherwise. Consumer comments were identified as queries if they were interrogative. We used the software LIWC2015 (Pennebaker et al. 2015) to identify such comments. LIWC is an automated text classification software that has been widely used in psychology and linguistics (Tausczik and Pennebaker, 2010). In addition to the reactive and proactive types of interventions, brands often personalize their interventions on Facebook by mentioning the name of a specific consumer. On Facebook, this practice is called "user tagging". Figure 1 illustrates an example of personalized brand intervention using Facebook's user tagging feature.

Figure 6. Example of personalized brand intervention using user tagging

Measuring the timing of brand interventions. We measured the timing of reactive brand interventions as the time lag between the brand intervention and the consumer comment to which the brand replies. The timing of "proactive" brand interventions, when not replying to a specific comment, was the time lag between the intervention and the start of the conversation (i.e., the first consumer comment). The timing of brand interventions captures whether the interventions are quick or delayed in response to consumers' comments.

Measuring the emotions of consumer conversations. To assess the emotional engagement in consumer conversations, we conducted a sentiment analysis which is regularly used by marketers for a rapid, scalable and effective way to gauge consumers' feelings by analyzing their comments. As with classifying brand interventions, we used automated text analysis software LIWC2015 (Pennebaker et al. 2015), which also supports a sentiment lexicon for positive and negative emotions. For sentiment analysis the software calculates the relative frequency of words related to that polarity in a given text sample (e.g., the words "love", "nice", or "sweet" are counted as representatives of positive valence, while the words "hurt", "ugly", "nasty" are counted as representatives of negative valence). All comments within consumer-to-consumer conversation threads, totaling 1,706,656 comments, were classified as positive, negative or unknown (typically considered as neutral).

For each conversation C, the proportion of positive comments $PP(C)$ and the proportion of negative comments $PN(C)$ were then combined into a single emotional score following Nicholls and Song (2010) as follows:

$$Score(C) = \frac{PP(C) - PN(C)}{PP(C) + PN(C)}$$

The value of $Score(C)$ ranges between -1 and +1. Conversations with higher proportions of negative comments compared to positive comments received scores closer to -1 whereas conversations with higher proportions of positive comments received scores closer to +1.

Measuring the effects of brand interventions on consumer emotional engagement. For each brand intervention BI_x in a consumer-to-consumer conversation, we measured prior and subsequent positive (negative) emotional engagement. To do that, we identified two sets of comments: $C^{\ll}_{BI_x}$ corresponding to the consumer comments prior to brand intervention BI_x and $C^{\gg}_{BI_x}$ corresponding to the subsequent consumer comments. We measured emotional engagement *before* brand intervention by computing $PP(C^{\ll}_{BI_x})$ as the proportion of positive comments and $PN\left(C^{\ll}_{BI_x}\right)$ *as* the proportion of negative comments within the set of comments $C^{\ll}_{BI_x}$ prior to BI_x. We also measured emotional engagement *after* brand intervention as the proportion of positive comments $PP(C^{\gg}_{BI_x})$ and the proportion of negative comments $PN(C^{\gg}_{BI_x})$ in the set of comments $C^{\gg}_{BI_x}$ subsequent to BI_x.

Given that multiple brand interventions can occur within the same conversation, the sets of prior comments $C^{\ll}_{BI_x}$ and subsequent comments $C^{\gg}_{BI_x}$ of a brand intervention BI_x had to be adjusted for any cumulative effect of prior and subsequent brand interventions within the same conversation. Figure 2 illustrates how such an adjustment was made using the two scenarios of a single versus a multiple brand interventions.

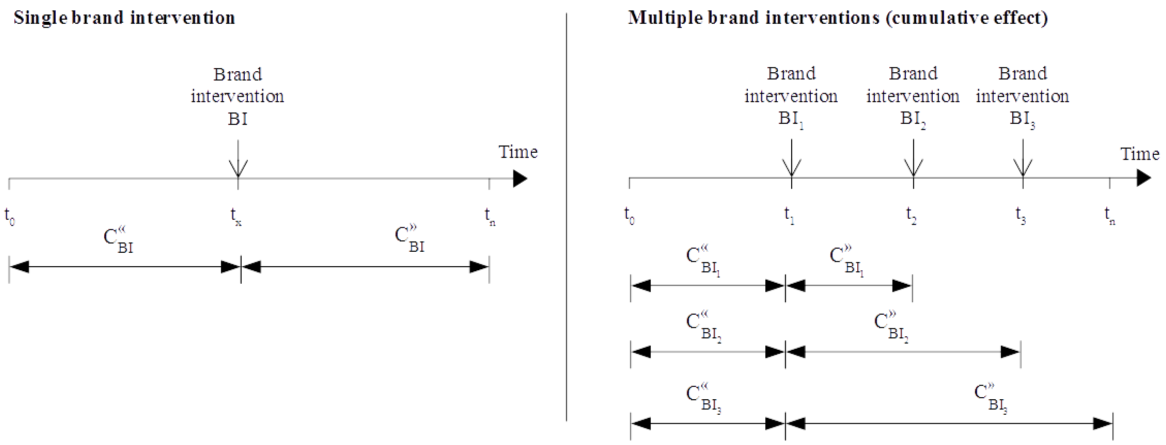


Figure 7. Example of single and multiple brand interventions

With a single brand intervention BI, $C_{BI}^{\ll}$ and $C_{BI}^{\gg}$ are simply the two sets of comments before and after the intervention. With three brand interventions, BI_1 then BI_2 and then BI_3 in the same conversation, $C_{BI_3}^{\ll}$ corresponds to the set of comments prior to the *first* brand intervention BI_1. This adjusts the interval of $C_{BI_3}^{\ll}$ to exclude comments affected by other brand interventions (for instance BI_1 and BI_2). $C_{BI_3}^{\gg}$ is set to be the set of comments subsequent to BI_1 and corresponds to *all* comments that occurred *after* brand interventions have commenced. The principle for adjusting $C_{BI_3}^{\gg}$ is to retain *all* comments affected by *any prior* brand intervention and exclude those affected by *any subsequent* brand interventions.

Once $C_{BI}^{\ll}$ and $C_{BI}^{\gg}$ were identified for a given brand intervention BI, the measure of the effect of BI on consumer emotional engagement was calculated as the relative emotional shift after brand intervention in terms of changes in the valence of consumer comments. Given that consumer comments can be positive, negative or neutral, an increase in the proportion of positive comments is not necessary related to a decrease in the proportion of negative consumer comments, and vice versa. Therefore, the emotional shift after a brand intervention comprises two separate measures reporting changes in the proportions of positive and negative consumer comments. The two measures were calculated as follows:

$$Shift^{+}(BI) = \frac{PP(C_{BI}^{\gg}) - PP(C_{BI}^{\ll})}{PP(C_{BI}^{\gg}) + PP(C_{BI}^{\ll})}$$

$$Shift^{-}(BI) = \frac{PN(C_{BI}^{\gg}) - PN(C_{BI}^{\ll})}{PN(C_{BI}^{\gg}) + PN(C_{BI}^{\ll})}$$

$PP(C)$ is the proportion of positive consumer comments in a conversation $C, and\ PN(C)$ is the proportion of negative consumer comments in a conversation C. The numerators measure the difference between the proportions of positive, respectively negative, consumer comments before and after brand intervention. The denominators measure the total of positive, respectively negative, consumer comments before and after brand intervention. Therefore, the values of the emotional shift $Shift^{+}(BI)$ for positive consumer comments and the emotional shift $Shift^{-}(BI)$ for negative consumer comments after a brand intervention BI lie between -1 and +1. The closer to +1, the greater emotional shift in one direction, and the closer to -1, the greater emotional shift in the opposite direction which means if all consumer comments prior to a brand intervention BI were negative, and all subsequent consumer comments were positive, $Shift^{+}(BI) = +1$ (shift from none of the comments before brand intervention being positive to all of the comments after the intervention are positive) and $Shift^{-}(BI) = -1$ (shift from all the comments being negative before brand intervention to none of the comments after the intervention are negative).

The scaling of emotional engagement adjusts for the position of the brand intervention within the conversation by using relative values (proportion) of positive and negative consumer comments rather than absolute values. Furthermore, the shift is relative to previous values. As such, a decrease from 10% to 5% of negative consumer comments after a brand intervention would be a relative shift of negative emotional engagement of -0.33.

Results

Descriptive Statistics. The dataset consists of 24,557 consumer conversations within which 64,347 brand interventions occurred. Table 1 provides detailed descriptive statistics. Most conversations contain only one brand intervention (63.15%). Most brand interventions are proactive (78.79%) and less than a quarter (19.12%) are personalized. Consumer emotional engagement before brand intervention tends to be more positive (42.9% on average) than negative (7.1% on average) which is consistent with findings of prior research (Chevalier and Mayzlin, 2006; Hennig-Thurau et al., 2010; Hoffman and Novak, 2011; Wirtz et al., 2013).

Table 17. Descriptive statistics of brand interventions and consumer emotional engagement

Brand intervention type	*# Observ.*	*Proportion*		
All	*64,347*	*100%*		
Reactive	13,648	21.21%		
Proactive	50,699	78.79%		
Personalized	12,305	19.12%		

Non-Personalized	52,042	80.88%		
Brand intervention time lag (in hours)	*Min*	*Mean*	*Max*	*SD*
All	0.00	23.73	7,149	105.80
Reactive	0.00	25.71	5,976	123.27
Proactive	0.00	23.08	7,149	99.39
Frequency of brand interventions per conversation	1.00	2.65	686	8.70
Emotional valence before and after brand intervention	*Before brand intervention*		*After brand intervention*	
	Mean	SD	Mean	SD
Proportion of positive comments	0.429	0.335	0.472	0.378
Proportion of negative comments	0.071	0.164	0.069	0.186
Emotional shift	*Min*	*Mean*	*Max*	*SD*
$Shift^{+}$ (-1 to +1)	-0.500	0.077	1.000	0.297
$Shift^{-}$ (-1 to +1)	-0.500	0.009	1.000	0.148

Dynamics of brand interventions on consumer emotional engagement. Figure 3 provides a snapshot of a typical consumer-to-consumer conversation on a Facebook brand page showing how a single brand intervention affects consumer emotional engagement over time. The graph shows how the proportion of both positive and negative comments shift over time with a substantial intensification of consumer activity directly after the brand intervention. In this case, there is an increase in positive consumer comments over time.

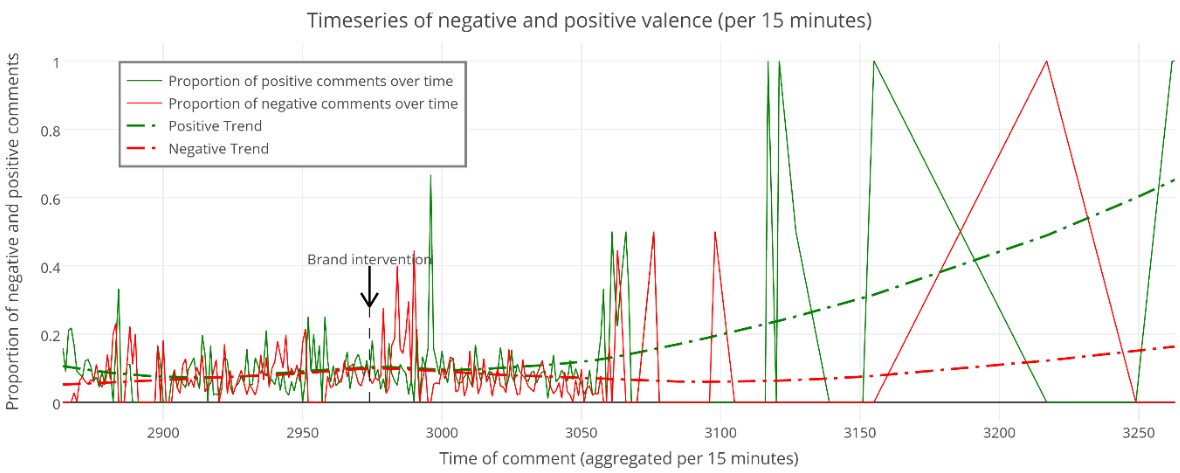


Figure 8. Example of a brand intervention in a single consumer-to-consumer conversation

To examine how brand interventions influence consumer emotional engagement for the entire dataset, we plot the relationship between the emotional score of consumer comments prior to brand intervention $Score(C_{BI}^{\ll})$ on the x-axis and the emotional shifts $Shift^{-}(BI)$ *and* $Shift^{+}(BI)$ after brand interventions on the y-axis. Figure 4 shows the shifts in negative emotions $Shift^{-}(BI)$ and Figure 5 shows the shifts in positive emotions. In both figures the emotional scores $Score(C_{BI}^{\ll})$ on the x-axis are grouped from highly negative comments to highly positive comments.

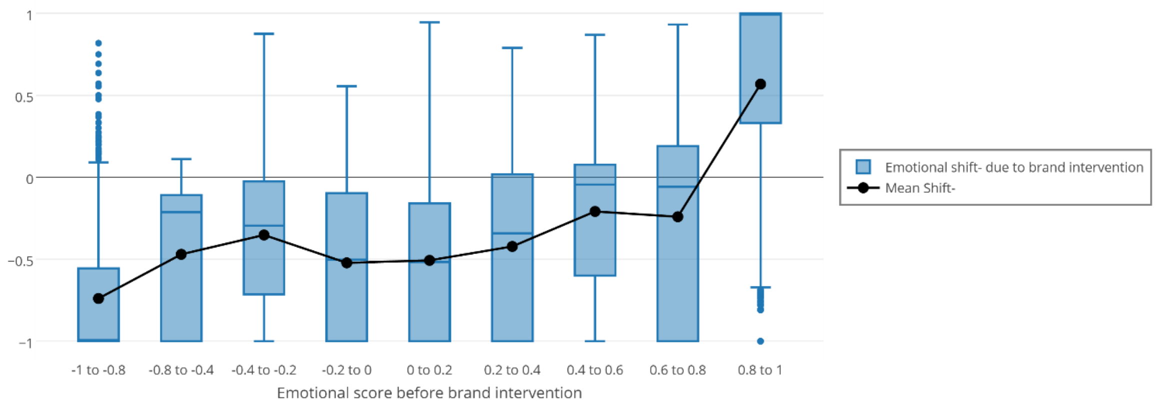


Figure 9. Effect of brand intervention on consumer negative emotional engagement

Figure 4 shows that brand interventions contribute to reducing subsequent negative consumer comments. In particular, when the emotional score of consumer comments before brand intervention is low (-1≤ $Score(C_{BI}^{\ll}) < 0.8$), the shift in negative emotions $Shift^{-}(BI)$, is negative and decreasing (y-axis). These results demonstrate that brand interventions in most cases mitigate the effect of negative consumer comments over time. However, when brands intervene in highly positive consumer conversations ($0.8 < Score(C_{BI}^{\ll}) \leq 1$), consumer negative comments tend to increase after the intervention. A possible explanation for this counter intuitive result could be that when brands reply to negative consumer comments, those comments are displayed as top comments. Top comments are always visible under a Facebook post and are most likely to have an impact on other consumers. Thus, they play a role in stimulating further consumer emotional engagement. The comment ranking algorithm introduced by Facebook back in 2012 helps to identify the top comments as the "most relevant comments" in a conversation associated with a Facebook post. Among the criteria Facebook is using for comment ranking, brand replies are of particular importance[2].

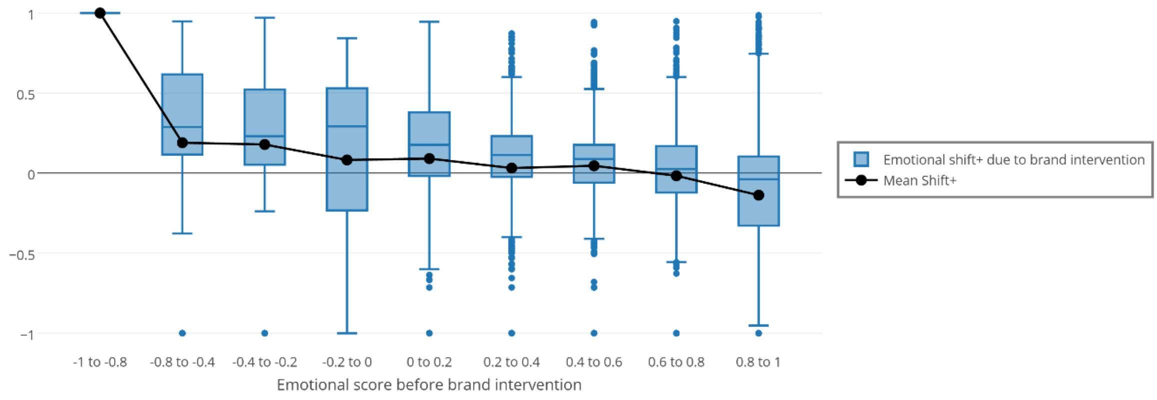


Figure 10. Effect of brand intervention on consumer positive emotional engagement

Figure 5 shows that brand interventions also help in increasing positive consumer comments in consumer-to-consumer conversation. Brand interventions have a higher impact on positive comments for conversations with lower emotional scores. Moreover, brand interventions in highly positive consumer conversations ($0.8 < Score(C_{BI}^{\ll}) \leq 1$) attenuate positive consumer engagement. One plausible explanation to this counter intuitive result might be that when brands intervene in highly positive consumer-to-consumer conversations, their interventions may be perceived by consumers as an attempt from an intrusive actor trying to dominate and control the conversation, thus creating unpleasant feelings of suspicion and mistrust (Porter and Donthu, 2008).

Effectiveness of brand intervention strategies. We use an analysis of covariance (ANCOVA) to investigate the effect of various brand intervention strategies on consumer emotional engagement. We test the effects of brand proactivity, personalization, timing and frequency on "the shift in positive emotions after brand intervention" ($Shift^{+}$) while controlling for the emotion score before brand intervention. A similar analysis is also conducted on the shift in negative emotions after brand intervention ($Shift^{-}$). Results of the two

[2] https://www.facebook.com/help/539680519386145

ANCOVA analyses are in Table 2 and the comparative outcomes of the brand interventions strategies are depicted in Table 3.

Table 18. Results of ANCOVA predicting $Shift^{+}$

Results of ANCOVA predicting $Shift^{+}$	**SS**	**DF**	**MS**	**F**	**p value**
Proactive brand intervention	1.66	1	1.66	14.40	0.0001
Personalized brand intervention	0.22	1	0.22	1.95	0.1623
Brand intervention time lag	0.06	1	0.06	0.51	0.4759
Frequency of brand interventions	19.77	1	19.77	171.54	<0.0001
Valence score prior to brand intervention (Control)	613.86	1	613.86	5327.42	<0.0001
Results of ANCOVA predicting $Shift^{-}$	**SS**	**DF**	**MS**	**F**	**p value**
Proactive brand intervention	21.5	1	21.5	54.71	<0.0001
Personalized brand intervention	14.1	1	14.1	35.99	<0.0001
Brand intervention time lag	11.2	1	11.2	28.49	<0.0001
Frequency of brand interventions	1.2	1	1.2	2.98	0.0843
Valence score prior to brand intervention (Control)	3781.4	1	3781.4	9623.09	<0.0001

Note. SS = Sum of Squares; DF = Degrees of Freedom; MS = Mean Squares.

Table 19. Mean $Shift^{+}$ and Mean $Shift^{-}$ per brand intervention strategy, timing and frequency

	Proactive	vs.	Reactive	Personalized	vs.	Non-Personalized
$Shift^{+}$	0.10		0.09	0.15		0.09
$Shift^{-}$	0.10		0.16	0.19		0.10
	Single	vs.	Multiple	Quick (first intervention lag < 12 hours)	vs.	Delayed (first intervention lag ≥ 12 hours)
$Shift^{+}$	0.05		0.10	0.04		-0.02
$Shift^{-}$	-0.17		0.14	-0.001		-0.45

Effectiveness of brand intervention at generating more positive consumer engagement. The ANCOVA results show that the interaction of $Shift^{+}$ and proactive brand interventions is significant (F(1, 23826)=14.40, p=0.0001). Follow-up comparisons show that proactive brand interventions lead to more positive consumer emotional engagement than reactive brand interventions ($M_{Proactive}$=0.10 vs. $M_{Reactive}$=0.09). However, the results show no significant differences between personalized and non-personalized brand interventions on $Shift^{+}$. Additionally, the timing of brand interventions has no significant effect on positive consumer emotional engagement. Nevertheless, the interaction of $Shift^{+}$ and the frequency of brand interventions is significant (F(1, 23826)=171.54, p<0.0001). Follow-up comparisons show that multiple brand interventions per conversation lead to more positive consumer emotional engagement than a single brand interventions (M_{Single}=0.05 vs. $M_{Multiple}$=0.10).

Effectiveness of brand intervention at reducing negative consumer engagement.

The ANCOVA results show that proactive brand interventions is significantly related to $Shift^{-}$ (F(1, 23826)=54.71, p=<0.0001). Follow-up comparisons indicate that proactive brand interventions lead to weaker shift in negative consumer emotional engagement than reactive brand interventions ($M_{Proactive}$=0.10 vs. $M_{Reactive}$=0.16). This implies that proactive brand intervention contribute in reducing subsequent negative consumer comments. In addition, personalized brand interventions lead to significantly higher negative consumer emotional engagement (F(1, 23826)=35.99, p=<0.0001, $M_{Personalized}$=0.19 vs. $M_{Non\text{-}personalized}$=0.10). A possible explanation for this finding could be that non-personalized brand interventions would be perceived positively by a wider audience than personalized interventions. While the frequency of brand intervention does not have significant interaction with $Shift^{-}$, the timing of brand interventions significantly affects negative consumer emotional engagement (F(1, 23826)=28.49, p=<0.0001). In particular, delayed brand interventions are found to be associated with lower but stronger shift in negative consumer comments than quicker brand interventions (M_{Quick}=-0.001 vs. $M_{Delayed}$=-0.45). This finding indicates that delayed brand intervention leads to a much stronger negative shift in negative comments seemingly suggesting that brands would recover much stronger with a delayed brand intervention strategy. A possible explanation for this finding is that quick interventions are less likely to take consumers' issues seriously and solve consumer's problems or respond thoroughly to their inquiries (van Laer and De Ruyter, 2010), as most quick interventions are acknowledgements of reception of consumer feedback. The findings suggest that such quick interventions do not help mitigate negative consumer comments (M_{Quick}=-0.001). Instead, delayed interventions are found to have the strongest effect on reducing negative consumer engagement ($M_{Delayed}$=-0.45).

Discussion and conclusion

Using a large behavioral dataset from 2,740 Facebook brand pages across 25 industry sectors, we empirically demonstrate the effects of brand interventions on emotional dynamics in online consumer-to-consumer conversations. Brand interventions affect consumer emotional engagement over time. The effects are stronger on negative consumer emotional engagement and in most cases brand interventions mitigate the effect of negative consumer comments over time. Such effects are however weaker for positive consumer conversations. Moreover, our findings suggest that when brands intervene in negative conversations, they should be proactive but should not personalize their responses. Delayed interventions in negative conversations generate a greater shift in consumer emotions and have the strongest effect on reducing negative consumer engagement. Finally, the effects of single or multiple interventions is not statistically different, suggesting that "less is more" at least from resources point-of-view. These findings suggest that brand managers have to play a balancing act when intervening in consumer-to-consumer conversations to attenuate negative consumer comments and increase positive consumer comments as brand interventions are more effective in negative consumer conversation than the positive ones.

Despite these contributions, this research entails some limitations that could be the focus of future research. First, our results are based on Facebook conversations, therefore, caution is warranted in generalizing the findings to other online social media platforms such as Twitter, Google+, LinkedIn or Tumblr. Future studies may wish to examine the dynamics of brand intervention effects in other social networking platforms, widening the scope of this research. Second, with the staggering uptake of mobile social networking, as 1.57 billion monthly active users in 2016 are accessing Facebook on their mobile devices, a new shift in the paradigm of consumer-brand interactions is announced. In particular, with the recent introduction of chat bots by Facebook, the inherently personal nature of consumer-to-consumer real-time interaction on Facebook Messenger is becoming a brand platform where brands can interact in real time with consumers instead of intervening sporadically in consumer conversations. Mobile social networking would be an interesting avenue for future research on the dynamics of real-time brand interventions in consumer conversations.

References

Baumeister, Roy F., Kathleen D. Vohs, C. Nathan Dewall, and Liqing Zhang (2007), "How Emotion Shapes Behavior: Feedback, Anticipation, and Reflection, Rather than Direct Causation," *Personality & Social Psychology Review*, 11 (2), 167-20.

Brodie, R. J., Ilic, A., Juric, B., & Hollebeek, L. (2013). Consumer engagement in a virtual brand community: An exploratory analysis. *Journal of Business Research*, 66(1), 105-114.

Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of marketing research*, 43(3), 345-354.

Chiou, J. S., & Cheng, C. (2003). Should a company have message boards on its web sites? *Journal of Interactive Marketing*, 17(3), 50-61.

Dellarocas, C. (2003). The digitization of word of mouth: Promise and challenges of online feedback mechanisms. *Management science*, 49(10), 1407-1424.

Dellarocas, C. (2006). Strategic manipulation of internet opinion forums: Implications for consumers and firms. *Management science*, 52(10), 1577-1593.

Dholakia, U. M., Blazevic, V., Wiertz, C., & Algesheimer, R. (2009). Communal service delivery how customers benefit from participation in firm-hosted virtual P3 communities. *Journal of Service Research*, 12(2), 208-226.

Fournier, S., & Avery, J. (2011). The uninvited brand. Business horizons, 54(3), 193-207.

Geylani, T., Inman, J. J., & Hofstede, F. T. (2008). Image reinforcement or impairment: The effects of co-branding on attribute uncertainty. *Marketing Science*, 27(4), 730-744.

Goh, K. Y., Heng, C. S., & Lin, Z. (2013). Social media brand community and consumer behavior: Quantifying the relative impact of user-and marketer-generated content. *Information Systems Research*, 24(1), 88-107.

Gummerus, J., Liljander, V., Weman, E., & Pihlström, M. (2012). Customer engagement in a Facebook brand community. *Management Research Review*, 35(9), 857-877.

Hareli, S., & Rafaeli, A. (2008). Emotion cycles: On the social influence of emotion in organizations. *Research in organizational behavior*, 28, 35-59.

Hennig-Thurau, T., Malthouse, E. C., Friege, C., Gensler, S., Lobschat, L., Rangaswamy, A., & Skiera, B. (2010). The impact of new media on customer relationships. *Journal of service research*, 13(3), 311-330.

Hoffman, D. L., & Novak, T. P. (2011). Marketing Communication in a Digital Era. *Marketing Management*, 20(3), 36.

Homburg, C., Ehm, L., & Artz, M. (2015). Measuring and managing consumer sentiment in an online community environment. *Journal of Marketing Research*, 52(5), 629-641.

Kandampully, J. (2013). Managing brands and customer engagement in online brand communities. *Journal of Service Management*, 24(3), 223-244.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business horizons*, 53(1), 59-68.

King, R. A., Racherla, P., & Bush, V. D. (2014). What we know and don't know about online word-of-mouth: A review and synthesis of the literature. *Journal of Interactive Marketing*, 28(3), 167-183.

Kozinets, R. V., De Valck, K., Wojnicki, A. C., & Wilner, S. J. (2010). Networked narratives: Understanding word-of-mouth marketing in online communities. *Journal of marketing*, 74(2), 71-89.

Ludwig, S., De Ruyter, K., Friedman, M., Brüggen, E. C., Wetzels, M., & Pfann, G. (2013). More than words: The influence of affective content and linguistic style matches in online reviews on conversion rates. *Journal of Marketing*, 77(1), 87-103.

Moe, W. W., & Trusov, M. (2011). The value of social dynamics in online product ratings forums. *Journal of Marketing Research*, 48(3), 444-456.

Muntinga, D. G., Moorman, M., & Smit, E. G. (2011). Introducing COBRAs: Exploring motivations for brand-related social media use. *International Journal of Advertising*, 30(1), 13-46.

Pennebaker, J.W., Boyd, R.L., Jordan, K., & Blackburn, K. (2015). The development and psychometric properties of LIWC2015. *Austin, TX: University of Texas at Austin*.

Porter, C. E., & Donthu, N. (2008). Cultivating trust and harvesting value in virtual communities. *Management Science*, 54(1), 113-128.

Rishika, R., Kumar, A., Janakiraman, R., & Bezawada, R. (2013). The effect of customers' social media participation on customer visit frequency and profitability: an empirical investigation. *Information systems research*, 24(1), 108-127.

Scarduzio, J. A., & Tracy, S. J. (2015). Sensegiving and sensebreaking via emotion cycles and emotional buffering how collective communication creates order in the courtroom. *Management Communication Quarterly*, 0893318915581647.

Schamari, J., & Schaefers, T. (2015). Leaving the home turf: How brands can use webcare on consumer-generated platforms to increase positive consumer engagement. *Journal of Interactive Marketing*, 30, 20-33.

Schau, H. J., Muñiz Jr, A. M., & Arnould, E. J. (2009). How brand community practices create value. *Journal of marketing*, 73(5), 30-51.

Schlosser, A. E. (2005). Posting versus lurking: Communicating in a multiple audience context. *Journal of Consumer Research*, 32(2), 260-265.

Seraj, M. (2012). We create, we connect, we respect, therefore we are: intellectual, social, and cultural value in online communities. *Journal of Interactive Marketing*, 26(4), 209-222.

Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of language and social psychology*, 29(1), 24-54.

van Laer, T., & De Ruyter, K. (2010). In stories we trust: How narrative apologies provide cover for competitive vulnerability after integrity-violating blog posts. International Journal of Research in Marketing, 27(2), 164-174.

van Noort, G., & Willemsen, L. M. (2012). Online damage control: The effects of proactive versus reactive webcare interventions in consumer-generated and brand-generated platforms. *Journal of Interactive Marketing*, 26(3), 131-140.

Vermeulen, I. E., & Seegers, D. (2009). Tried and tested: The impact of online hotel reviews on consumer consideration. *Tourism management*, 30(1), 123-127.

Vivek, S. D., Beatty, S. E., & Morgan, R. M. (2012). Customer engagement: Exploring customer relationships beyond purchase. *Journal of Marketing Theory and Practice*, 20(2), 122-146.

Wirtz, J., den Ambtman, A., Bloemer, J., Horváth, C., Ramaseshan, B., van de Klundert, J., Gurhan Canli, Z., & Kandampully, J. (2013). Managing brands and customer engagement in online brand communities. *Journal of Service Management*, 24(3), 223-244.

Appendix B

Paper published at Journal of Consumer Marketing, 2017

SOCIAL MEDIA SENTIMENT ANALYSIS: LEXICON VERSUS MACHINE LEARNING

Chedia Dhaoui, Macquarie University, Australia, chedia.dhaoui@mq.edu.au

Cynthia M. Webster, Macquarie University, Australia, cynthia.webster@mq.edu.au

LayPeng Tan, Macquarie University, Australia, laypeng.tan@mq.edu.au

Abstract

Purpose: With the soaring volumes of brand-related social media conversations, digital marketers have extensive opportunities to track and analyze consumers' feelings and opinions about brands, products or services embedded within consumer generated content (CGC). These "Big Data" opportunities render manual approaches to sentiment analysis impractical and raise the need to develop automated tools to analyze consumer sentiment expressed in text format. This paper evaluates and compares the performance of two prominent approaches to automated sentiment analysis applied to CGC on social media and explores the benefits of combining them.

Design/methodology/approach: A sample of 850 consumer comments from 83 Facebook brand pages are used to test and compare lexicon-based and machine learning approaches to sentiment analysis, as well as their combination, using the LIWC2015 lexicon and RTextTools machine learning package.

Findings: Results show the two approaches are similar in accuracy, both achieving higher accuracy when classifying positive sentiment than negative sentiment. However, they differ substantially in their classification ensembles. The combined approach demonstrates significantly improved performance in classifying positive sentiment.

Research limitations/implications: Further research is required to improve the accuracy of negative sentiment classification. The combined approach needs to be applied to other kinds of CGCs on social media such as tweets.

Practical implications: The findings inform decision making around which sentiment analysis approaches (or a combination thereof) is best to analyze CGC on social media.

Originality/value: This study combines two sentiment analysis approaches and demonstrates significantly improved performance.

Keywords: Social media; Sentiment analysis; Consumer generated content

Paper type: Research paper

Introduction

The considerable advancements of social media during the last decade, along with the profusion of digital channels, such as social networking sites (e.g., Facebook), microblogs (e.g., Twitter) and media sharing (e.g., Instagram or Youtube), have revolutionized not only the way brands communicate with their consumers, but also the roles of consumers in the marketing process. In a sense, social media gives consumers the same, if not more voice than brands, disrupting marketing processes and creating serious dilemmas and challenges for marketers (Constantinides et al., 2009). Brand managers can no longer afford to ignore their consumers' important online voice (Gensler et al., 2013). They are also offered new opportunities to tap into the unfettered consumer generated content (CGC) readily available on social media platforms. With digital marketing now treated as a "many-to-many conversation" between businesses and consumers as well as among consumers themselves (Lusch et al., 2010), the traditional one-way business-to-consumers transmissions is becoming obsolete.

A recent trend in the digital marketing analytics sphere is to track and analyze consumers' feelings and opinions about specific brands, products or services attributed to the CGC on social media (Hemann and Burbary, 2013). The objective is to classify positive and negative CGC, typically text-based, according to some manual or automated classification methods. For example, marketers can retrieve timely consumer feedback on a new product by evaluating consumer sentiment expressed in the comments on a Facebook post or in tweets with a specific hashtag related to the product.

Given the large volume of CGC, commonly referred to as “Big Data” that has grown along with the uptake of social media platforms, the qualitative manual analysis of consumers’ sentiment conveyed in online brand related content is no longer practical. To put this into perspective, Twitter generates over 500 million tweets each day and there are 4.75 billion pieces of content per day on Facebook. This raises the need to develop automated tools for identifying and analyzing consumer sentiment expressed in text (Wang et al., 2012).

Two prominent approaches to automated sentiment analysis exist. Classification using a lexicon of weighted words (Taboada et al., 2010) is a widely used approach to sentiment analysis in the marketing research community (Bolat and O’Sullivan, 2017) as it does not require any pre-processing or training of the classifier. Alternatively, the machine learning approach to sentiment analysis, also described as a supervised learning approach, is often reported to be more accurate (Pang et al., 2002; Chaovalit and Zhou, 2005) and has also been used in marketing research (Pathak and Pathak-Shelat, 2017). However, the machine learning approach requires a training phase that is either conducted by the researchers themselves or by the sentiment software provider. As each of these methods has its advantages and limitations, marketers and researchers need to carefully verify the accuracy of the classification (Brown et al., 1990) to avoid acting on inaccurate data analysis outcomes (Canhoto and Padmanabhan, 2015). Furthermore, given the wide range of social media platforms and their specificities as to what type of content consumers can create (e.g. Facebook comments, Twitter tweets, the use of emoticons, emojis, hashtags, the use of abbreviations, slang language, etc.), existing sentiment analysis approaches, typically tested on well-formed English language texts, require careful validation before being used by marketers on social media data.

The purpose of this paper is to compare the lexicon-based approach and the machine learning approach to address three research questions: 1) Are these two existing sentiment analysis techniques appropriate for the analysis of social media conversations? 2) To what extent do the results from the two approaches differ when used on social media conversations? 3) Does a combined approach improve the overall accuracy of the sentiment classification of social media conversations? To answer these questions, we first summarize the challenges with regards to text classification methods for sentiment analysis used today on social media data. We then outline the research method and empirically evaluate the lexicon-based, machine learning and combined approaches using a large sample of consumer generated comments (CGC) on Facebook brand pages.

Literature

Studying the language people use in order to better understand their thoughts and behaviors is not new in the social sciences (Krippendorff, 2012). Sentiment has long been measured using self-reported data in consumer surveys such as the Michigan Consumer Sentiment Surveys. However, the use of self-reported data has its limitations, as do most self-reported data. With surveys, marketing researchers rely on consumers' abilities to accurately recall their felt experiences, which may be highly variable and difficult to verbalize and reconstruct (Cooke and Buckley, 2008; Nabi and Oliver, 2009). In contrast, with experiments, there are concerns relating to the artificial circumstances in which data are gathered, which may constrain consumers' emotional responses (Nabi, 2007).

Today, social media platforms are popular vehicles to study consumer sentiment on a large scale and within a natural setting (Kivran-Swaine et al., 2012) due to the significant share of online conversations expressing consumers' thoughts, feelings and opinions about products and brands (Jansen et al., 2009). The analysis of sentiment in textual content often relies on simple sentiment annotation tasks during which annotators must determine whether a sentence is positive, negative, or neutral (Rosenthal et al., 2015; Mohammad et al., 2015). Given the large volume of social media content, manual sentiment annotation is impractical.

Supported by most automated text classification tools, sentiment analysis is regularly used by marketers for a computer-supported, rapid, scalable and effective way of gauging consumer's sentiment (Murdough, 2013). Automated sentiment analysis receives increasing attention from both academia and industry (Chen and Zimbra, 2010), and has become one of the key techniques for handling large volumes of social media data. Typically, automated sentiment analysis techniques are used to classify any text-based document into predefined categories reflecting the polarity of sentiment referred to in the text. Recently, Canhoto and Padmanabhan (2015) have undertaken a comparative study of automated versus manual analysis of social media conversations. Their findings show low levels of agreement between manual and automated analysis, which is of "grave concern given the popularity of the latter in consumer research" (Canhoto and Padmanabhan, 2015, p.1141).

Automated classification of expressed sentiment in social media conversations is challenging for several reasons. First, identifying opinions and sentiments from text-based natural language requires a deep understanding of the explicit and implicit, regular and irregular, and syntactical and semantic language rules (Cambria et al., 2013). Furthermore, sentiment analysis faces difficulties in using natural language processing (NLP) on unstructured text, typical of social media conversations and CGC in general. For instance, CGC content typically reflects the instant and informal nature of communication on social media (Canhoto and Padmanabhan, 2015). The content typically is free-flowing text, casual in its word and grammar usage (Tirunillai and Tellis, 2014), commonly includes abbreviations, misspellings, emoticons, emojis and often uses SMS-like syntax, which current sentiment analysis methods do not adequately support. Additionally, particular platform features, like the 140 character limit for Twitter messages, impede the effectiveness of current automated sentiment analysis tools (Kiritchenko et al., 2014). Finally, the sheer volume of social media conversations is a significant challenge. Automated technologies turn that challenge into an opportunity by obviating the need for costly and risk-prone manual analysis, instead leveraging computerized procedures to draw insights from social media conversations.

Key approaches to automated sentiment classification

Selecting the right automated sentiment analysis method for social media data is crucial for achieving high accuracy in content classification. There exist two prominent approaches to text classification employed for sentiment analysis: lexicon-based and machine learning. Both approaches to sentiment classification typically classify any given text into positive, negative or neutral sentiment according to the polarity of the content.

The lexicon-based approach generally relies on a dictionary of opinion words, also known as a sentiment dictionary or a sentiment lexicon, to identify and determine sentiment orientation as positive or negative. A standard lexicon like the Linguistic Inquiry and Word Count (LIWC) includes such a sentiment dictionary. The compilation of a sentiment lexicon needs to be done manually requiring considerable effort and time. While different bodies of sentiment lexicon can be created for specific subject matters, sentiment words included in most lexicon-based analysis tools are not specific to a particular topic (Godbole et al., 2007). Like most lexicon-based methods, LIWC2015 typically analyses common words included in its dictionaries. Misspellings, colloquialisms, foreign words, and abbreviations are usually not in the dictionaries. Although LIWC2015 includes a few words frequently used in social media and text messaging (e.g., lol, 4ever, b4) and very basic punctuation-based emoticons such as :) and ;), it does not support emojis and emoticons, widely used on social media. Furthermore, the drawback of using the lexicon-based approach to sentiment analysis is that the polarity classification could vary across different domains. For example, the adjective “unpredictable” can have a positive orientation in a movie review but a negative orientation for a car’s steering abilities (Turney, 2002).

The machine learning approach uses a fraction of the full data as a manually classified training dataset and trains classifiers to learn by examples, thus “supervising” the classification and without relying on any prior lexicon. This approach typically trains sentiment classifiers using features such as unigrams or bigrams (Pang et al., 2002) by applying different learning techniques such as Naive Bayes, Maximum Entropy or Support Vector Machines. While machine learning methods that employ training datasets for automating data classification are advantageous, these methods still require manual labelling of training examples, which size and quality affect the performance of the trained model. High quality labelling of a large training dataset can be time consuming, while limiting the size of the training dataset leads to poorer classification accuracy. Furthermore, the sampling of the training dataset can have a significant impact on the performance of the trained model, depending on how many domains are represented.

The choice of which approach to use is crucial as it impacts the accuracy of the sentiment classification and needs to be carefully aligned with the type of data being analyzed (Chae, 2015). In general, using lexicon-based approaches has been shown to be less effective than machine learning models from training examples (Pang et al., 2002). However, opting for machine learning and ignoring the lexical knowledge in lieu of training data, may not be optimal. Several attempts to combine the two approaches have been conducted and reported in the literature, as illustrated in Table 1. These studies mainly use lexicon-based sentiment classification to label data and then use that labelled data as a training dataset to train a machine learning model (e.g., Sommar and Wielondek, 2015; Mudinas et al., 2012; Liu et al., 2011; Tan et al., 2008). Combining lexicon-based and machine learning approaches in such a way avoids having to manually classify data for training purposes. While successful at improving the classification accuracy compared to lexicon-based only, these combined approaches still do not outperform machine learning approaches trained with manually classified data (Sommar and Wielondek, 2015; Mudinas et al., 2012). Other attempts at combining sentiment analysis approaches (e.g., Prabowo and Thelwall, 2009) try multiple sentiment classifiers in sequence until one of them is successful at classifying sentiment either positive or negative. However, such approaches assume that sentiment classification has a binary outcome even when the content conveys both positive and negative sentiment.

Table 1. Previous studies combining lexicon based and machine learning approaches to sentiment analysis

	Data	Approach	Outcome
Sommar and Wielondek (2015)	Movie reviews	Use the outcome of lexicon-based classification to feed machine learning for improved performance and convenience in sentiment classification.	Combined approach outperforms the lexicon-based approach, in turn being outperformed by the learning based approach
Mudinas et al. (2012)	Software and movie reviews	Lexicon-based output is used to train a learning-based classifier.	Hybrid approach improves the accuracy of sentiment classification compared to lexicon only approach, but is less accurate than learning based methods only.
Liu et al. (2011)	Tweets	A classifier is trained using data given by the lexicon-based approach, instead of being labeled manually.	Combined approach improves recall compared to lexicon-based approach only.
Prabowo and Thelwall (2009)	Movie reviews, Product reviews, MySpace comments	Multiple sentiment classifiers are used in sequence so that if one classifier fails to classify a document, the classifier will pass the document onto the next classifier, until the document is classified or no other classifier exists.	The use of multiple classifiers in a sequential manner can result in better effectiveness than any individual classifier. However, documents were assigned to one sentiment only (binary classification), so that a document containing both conveying both positive and negative sentiment, was necessarily classified as either positive or negative.
Tan et al. (2008)	Movie Reviews, Computer Reviews, Education Reviews, and House Reviews.	Use a lexicon-based technique to label data; then learn a new supervised classifier based on the labeled data.	The experimental results indicate that proposed scheme could dramatically outperform "learn based" and "lexicon-based" techniques.

Comparative evaluation of automated sentiment analysis methods

In the present research, we compare lexicon-based and machine learning approaches to automated sentiment analysis. We aim to provide evidence of any performance difference between the two approaches and to offer empirically sound guidance as to which of the two approaches is best suited to the analysis of positive or negative valence in social media conversations. We then propose a combined approach, leveraging both lexicon-based knowledge and manually labelled data as a training dataset, and demonstrate the superior performance of the combined approach when applied to consumer generated conversations.

Data collection and sampling

Given the emotional value consumers attach to the fashion industry, we consider luxury fashion brands as an appropriate context for the current study (Theng et al., 2013). The Fashion 2015 Digital IQ Index® from L2 Inc was the source used to select a sample of 83 luxury fashion brands highly active on Facebook social media platform. Facebook Graph API was used to collect all posts published and their associated CGC in the form of comments on brand posts. Nine months' worth of data were collected and the most relevant comments on each post, also called "top comments", were identified using the comment ranking algorithm introduced by Facebook back in 2012.

Top comments are crucial as they reflect not only the most meaningful comments but also the most viewed comments. Indeed, top comments are always visible under a post which means top comments are the most likely to have an impact on other consumers, and thus play a role in stimulating sentiment laden brand conversations. They are also the most likely to require content analysis for marketers to gain insights into consumers' feelings, thoughts and opinions. A random sample of 850 top comments was manually classified as positive, negative or neither positive nor negative. The same sample was then classified automatically using lexicon-based and machine learning approaches and compared to the manual classification to assess their accuracy.

Sentiment classification

Lexicon based approach to sentiment analysis

LIWC2015 (Pennebaker et al., 2015), a text mining software, was used to conduct a lexicon based sentiment analysis of the data sample. LIWC enables a computerized analysis of the word used within a text and calculates the percentage of usage of sets of words that define different linguistic categories, generating an output measure for each of these categories. Among those categories, LIWC supports a sentiment lexicon for positive and negative sentiments. LIWC has been widely used in psychology and linguistics (Tausczik and Pennebaker, 2010). For each sentiment polarity the software calculates the relative frequency with which words related to that polarity occur in a given text sample. For example, the words "love", "nice", or "sweet" are counted as representatives of positive sentiment, while the words "hurt", "ugly", "nasty" are counted as representatives of negative sentiment.

Machine learning method for sentiment analysis

RTextTools is a machine learning package in R for automatic text classification. The package includes several algorithms for ensemble classification including maximum entropy, random forests, SVM, bagging, decision tree, etc. The objective of using a machine learning technique is to train classifiers from examples to perform the category assignments automatically. Since categories may overlap, each category is treated as a separate binary classification problem and content can belong to several categories simultaneously. This is commonly known as a supervised learning problem.

Half of the manually classified 850 top comments were used as a training dataset and the other half were reserved as a testing dataset, as it is recommended to use two different datasets for training and testing purposes. All machine learning algorithms supported by RTextTools R package were used to train models using the training dataset and test them using the testing dataset. For each supervised learning algorithms, the training dataset was fed into the algorithm to train and test two classifiers, one for positive sentiment and one for negative sentiment. Each distinct word, emoji or emoticon corresponds to a feature, with the number of times a feature occurs in the document as its value. The resulting representation scheme, generated by the RTextTools package in R, is a term matrix of 221 terms from the training dataset such as “cute”, “elegant”, “horrible”, etc., but also emojis and emoticons. Each of the trained classifiers uses a subset of those terms, automatically selected and weighted by the corresponding supervised learning algorithm.

The best performing classifiers were obtained using Maximum Entropy Modelling for predicting positive sentiment and the Bagging method for predicting negative sentiment. Maximum Entropy Modeling, or Maxent, uses a low-memory multinomial logistic regression with support for semi-automated text classification (Jurka, 2012). In the bagging classification approach (Breiman, 1996), each tree is constructed from a bootstrap (Efron and Tibshirani, 1993) sample drawn with replacement from the training dataset. Maxent and Bagging have been successfully applied to Natural Language Processing (Charniak, 1996) and are suitable for text categorization such as consumer comments on Facebook brand posts. In the remainder of the paper, these two top performing machine learning algorithms, Maxent for positive sentiment classification and Bagging for negative sentiment classification, are referred to as the machine learning approach.

Performance measures

We evaluated the performance of the two sentiment analysis approaches using a standard performance measure from the information retrieval literature (Van Rijsbergen, 1979; Sebastiani, 2002). Using the testing dataset of manually pre-classified CGC, along with the automated classification of the same dataset, we constructed two-by-two contingency tables of the counts of true positives (TP), false positives (FP), true negatives (TN) and false negatives (FN). On the one hand, true positives (true negatives) are the number of instances in which CGCs were accurately classified as positive (negative) by automated methods, using the manual classification as reference (correct classification). On the other hand, false positives (false negatives) are the number of instances in which CGCs were inaccurately classified as positive (negative) by automated methods. Note that content not classified as positive is not necessarily classified as negative. In fact, the same content can possibly be classified as both positive and negative if it refers to both valences at the same time.

To measure the performance of each approach, we used two commonly adopted measures of classification effectiveness namely, Precision $p = TP/(TP + FP)$ and Recall $r = TP/(TP + FN)$. Precision (p) of an automated classification method also known as positive predictive value, is the fraction of CGC for which automated and manual classifications match. A higher precision results from an automated classification that has a closer match with the manual classification. Recall (r) of an automated classification method, also known as sensitivity, is the proportion of positive (negative) CGCs that are manually classified as such and correctly classified by the automated method. A higher recall results from an automated classification method missing out on fewer positive (negative) CGCs, compared to manual classification.

There is an inherent tradeoff for a sentiment classification method between precision and recall as higher recall can be achieved at the price of very low precision. To provide a more balanced assessment of the performance of sentiment classification methods, the F score measure is used. The F score combines recall and precision in a single quantity as a weighted average (Cohen and Singer 1999), and is used as a single performance indicator that is high if both precision and recall are high and low if either precision or recall are low. In this paper, the F score equally weights precision and recall and corresponds to the following formula:

$$F\ score = 2 \times precision \times recall \ / \ (precision + recall)$$

The F score is bound between 0 and 1, and can be interpreted as a probability. The closer the score is to 1, the better. The practical significance of the F score is that it represents a single measure of classification performance. A high F score means that the classification method achieves both high precision and high recall.

Another performance indicator considered in this study is the accuracy of classification which is calculated as the proportion of both true positives (TP) and true negatives (TN) in comparison to false positives (FP) and false negatives (FN):

$$Accuracy = (TP + FP)/\,(TP + FP + TN + FN)$$

A higher accuracy indicates that the sentiment analysis approach is better able to classify positive and negative valence of CGC.

Results

The results in Table 2 show that lexicon-based and machine learning approaches to sentiment analysis perform very similar in terms of F scores for positive valence classification (F=0.77 and 0.78 respectively) as well as negative valence classification (F=0.45 and 0.47 respectively). The results directly contradict prior research regarding the performance of machine learning classification methods, claimed to be more accurate than lexicon-based approaches (Chaovalit and Zhou, 2005). The results also reveal that both approaches achieve higher accuracy when classifying positive valence than negative. The lower F scores for classifying negative valence, below 0.5, is explained by the well-recognized limitations of automated sentiment analysis methods when it comes to analyzing sarcasm, which is often a limitation for manual approaches too (Maynard and Greenwood, 2014). These results indicate that the existing sentiment analysis methods are appropriate for predicting positive valence, and limited for predicting negative valence, when applied to social media conversations.

Table 2. Evaluation of lexicon-based and machine learning approaches, as well as the proposed combined approach to sentiment analysis

	Precision	Recall (Sensitivity)	F score	Accuracy	True positives (TP)	False positives (FP)	True negatives (TN)	False negatives (FN)
Evaluation of positive valence classification (Total tested comments N=425)								
Manual	1	1	1	1	271	0	154	0
Lexicon-based	0.85	0.71	0.77	0.74	192	33	121	79
Machine learning	0.83	0.73	0.78	0.74	199	40	114	72
Combined approach	0.79	0.88	0.83	0.78	239	63	91	32

Evaluation of negative valence classification (Total tested comments N=425)								
Manual	1	1	1	1	75	0	350	0
Lexicon-based	0.31	0.81	0.45	0.65	61	135	215	14
Machine learning	0.54	0.41	0.47	0.83	31	26	324	44
Combined approach	0.31	0.91	0.46	0.62	68	154	196	7

Proposal of a combined approach to sentiment analysis

While the performances of both approaches to sentiment analysis are similar, the two approaches do differ in some classifications. Numerous methods are available to compare results of classification methods and estimate the agreement among them. One of the simplest but most effective of these procedures is to examine the intersections of the resulting classifications using UpSet plots and Venn diagrams (Lex et al., 2014). UpSet plots simplify the way intersections of multiple sets can be read using bar plots and are used to compare and contrast two or more sets in terms of the relationship between them. The relationship can be the intersection, union or complement. Figures 1 and 2 illustrate the relationship between the results of machine learning classification, lexicon-based classification and manual classification.

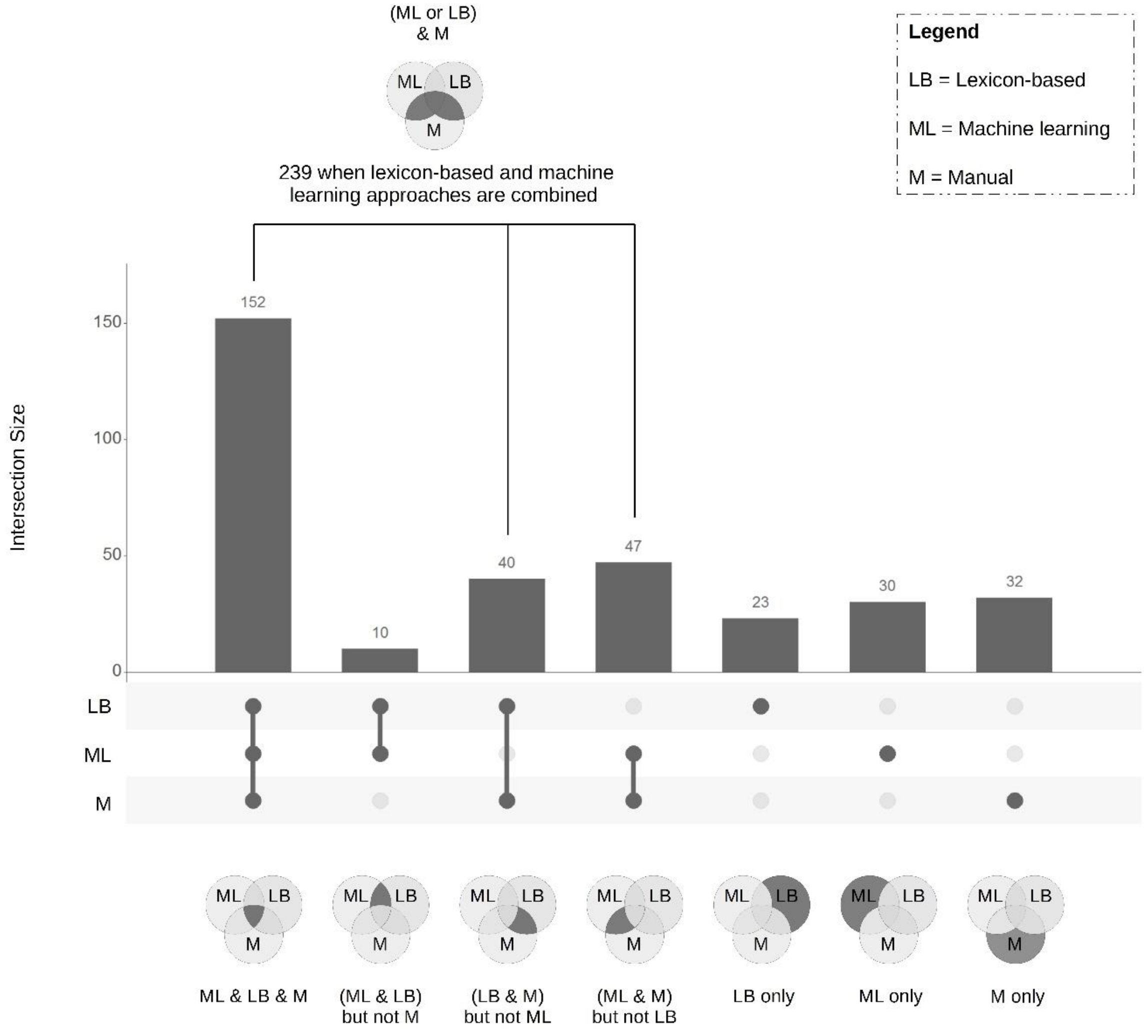


Fig. 1. UpSet plot illustrating the agreement/disagreement among lexicon based, machine learning and manual sentiment analysis for the classification of positive valence.

By matching manually classified comments and the automated classifications outcome, the lexicon-based and the machine learning approaches agree on 63.6% of correctly classified positive comments and 35.3% of correctly classified negative comments. Figures 1 and 2 further show the combination of both approaches significantly increases the number of consumer comments correctly classified. This indicates that one approach is complementing the other and that a combination of the approaches may produce a better outcome.

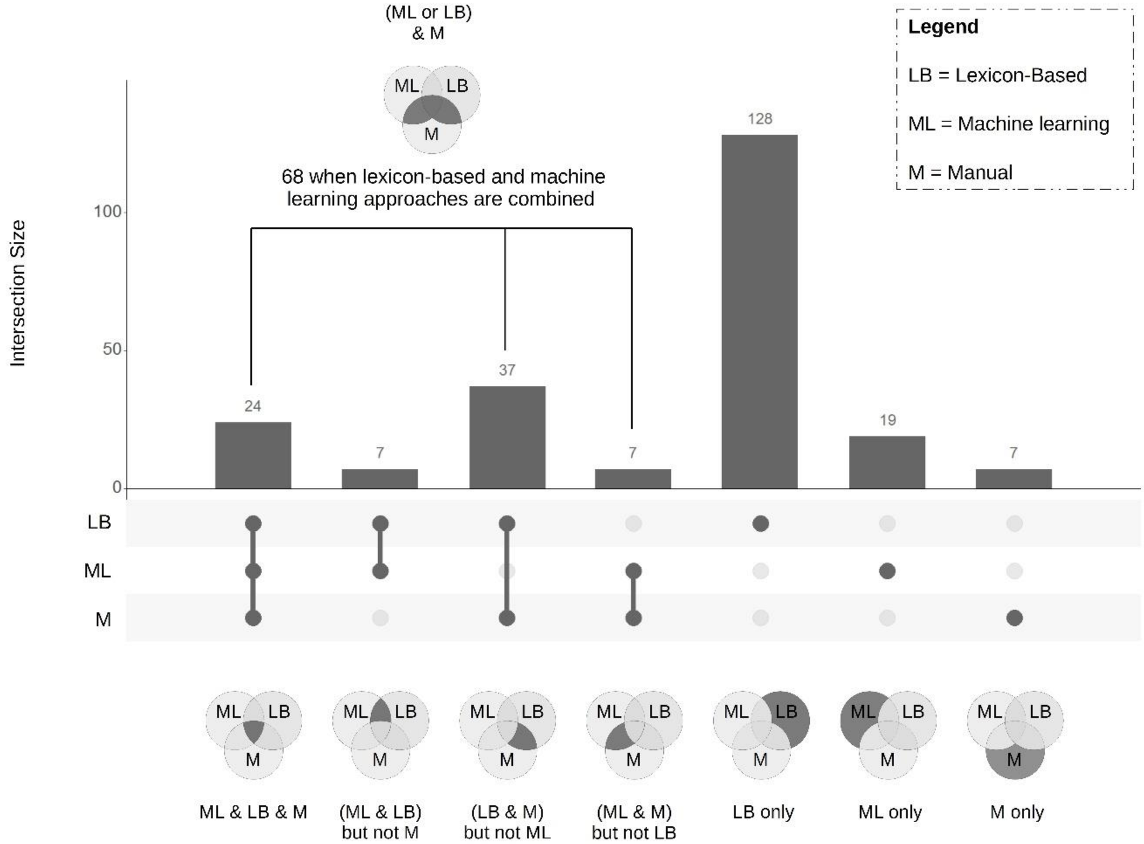


Fig. 2. UpSet plot illustrating the agreement/disagreement among lexicon based, machine learning and manual sentiment analysis for the classification of negative valence.

In this paper, we propose that such a combination can be as simple as using both approaches and combining their results. Thus, the motivation here is not to avoid manually labelling a training dataset, but rather to combine the strengths of lexicon-based and machine learning approaches for better accuracy of the results. Table 2 shows the results of the combined approach. The F-score for classifying positive sentiment increases substantially, scoring 0.83, but remains relatively the same for classifying negative sentiment at around 0.46 when using a combined approach. By combining the two approaches the overall performance of sentiment classification is greatly improved for classifying positive sentiment without penalizing the performance of classifying negative sentiment. This finding indicates that a combined approach is particularly valuable when marketers require sentiment analysis to accurately identify positive word of mouth.

Conclusions, limitations and future research

This study makes several contributions. First, we empirically test two prominent sentiment analysis approaches, namely lexicon-based and machine learning. The results indicate that, when applied on social media conversations, the two automated approaches have similar performance. Second, we demonstrate that combining the different approaches significantly improves classification performance in terms of precision and recall for positive sentiment. This finding suggests the great potential of a combined approach to gain deeper insights into positive social media conversations. Given the soaring volumes of brand-related social media conversations and the lack of guidance as to what tools are adequate to analyze such “Big Data”, our study fills a gap in the literature and adds to industry best practices. Our findings form the basis of decision making around which approach is best for marketers to analyze consumers’ social media conversations and how to best combine approaches to achieve better outcome.

Sentiment analysis is only one way to explore online conversations with other analytic approaches available for knowledge discovery. For these reasons, further research is required to guide marketers on how to select and match the various text analysis approaches with the different social media data sources to generate precise and accurate outcomes.

Among the variety of data analysis methods and techniques, the use of sentiment analysis for gauging public opinion is increasingly growing. Marketers tend to apply these methods without adequate evaluation of their effectiveness at classifying the sentiment valence of certain social media data sources, such as conversational data in the form of comments or tweets. In this paper, we have investigated the fit between the two main sentiment analysis approaches using conversational social media data consisting of Facebook consumer conversations.

Results from combining the two approaches are quite promising for positive sentiment analysis, but further research is required to improve the accuracy of negative sentiment analysis. To extend our study results, the combined approach needs to be applied to other kind of conversational data such as tweets and microblogs.

Although the fields of natural language processing, computational linguistics, and text analytics continue to mature, they arguably remain unable to match the ability of humans to take subtle aspects of the context into account and make fine distinctions when interpreting the content data (Conway, 2006), as empirically verified in this paper by the relatively low levels of accuracy for negative sentiments. Furthermore, this study, and most prior studies on sentiment analysis, are limited to the assessment of automated sentiment analysis applied to text only. It would be interesting to extend the study to other types of content such as images and videos using visual classification methods.

References

Bolat, E., & O'Sullivan, H. (2017), "Radicalising the marketing of higher education: learning from student-generated social media data", *Journal of Marketing Management*, Advance online publication, doi:10.1080/0267257X.2017.1328458

Breiman, L. (1996), "Bagging predictors", *Machine Learning*, Vol. 24 No. 2, pp. 123-140.

Brown, D., Taylor, C., Baldy, R., Edwards, G. and Oppenheimer, E. (1990), "Computers and QDA - can they help it? A report on a qualitative data analysis programme", *The Sociological Review*, Vol. 38 No. 1, pp. 134-150.

Cambria, E., Schuller, B., Xia, Y. and Havasi, C. (2013), "New avenues in opinion mining and sentiment analysis", *IEEE Intelligent Systems*, Vol. 28 No. 2, pp. 15-21.

Canhoto, A.I. and Padmanabhan, Y. (2015), " 'We (don't) know how you feel' - a comparative study of automated vs. manual analysis of social media conversations", *Journal of Marketing Management*, Vol. 31 No. 9-10, pp. 1141-1157.

Chae, B. K. (2015), "Insights from hashtag# supplychain and Twitter analytics: Considering Twitter and Twitter data for supply chain practice and research", *International Journal of Production Economics*, Vol. 165, pp. 247-259.

Chaovalit, P. and Zhou, L. (2005), "Movie review mining: A comparison between supervised and unsupervised classification approaches", in *System Sciences Proceedings of the 38th*

Annual Hawaii International Conference HICSS'05 in Hawaii, USA, 2005, IEEE, pp. 112c-112c.

Charniak, E. (1996), *Statistical Language Learning*. MIT press.

Chen, H. and Zimbra, D. (2010), "AI and opinion mining", *IEEE Intelligent Systems*, Vol. 25 No. 3, pp. 74-80.

Cohen, W.W. and Singer, Y. (1999), "Context-sensitive learning methods for text categorization", *ACM Transactions on Information Systems (TOIS)*, Vol. 17 No. 2, pp. 141-173.

Constantinides, E., Romero, C.L. and Boria, M.A.G. (2008), "Social media: a new frontier for retailers?", in Swoboda, B., Morschett, D., Rudolph, T., Schnedlitz, P. and Schramm-Klein, H. (Ed.), *European Retail Research*, Gabler Verlag, pp. 1-28.

Conway, M. (2006), "The subjective precision of computers: a methodological comparison with human coding in content analysis", *Journalism & Mass Communication Quarterly,* Vol. 83 No. 1, pp. 186-200.

Cooke, M. and Buckley, N. (2008), "Web 2.0, social networks and the future of market research", *International Journal of Market Research*, Vol. *50* No. 2, pp. 267-292.

Efron, B. and Tibshirani, R.J. (1994), *An Introduction to The Bootstrap*. CRC press.

Gensler, S., Völckner, F., Liu-Thompkins, Y. and Wiertz, C. (2013), "Managing brands in the social media environment", *Journal of Interactive Marketing*, Vol. 27 No. 4, pp. 242-256.

Godbole, N., Srinivasaiah, M. and Skiena, S. (2007), "Large-scale sentiment analysis for news and blogs", in *Proceedings of the International Conference on Weblogs and Social Media ICWSM in Boulder, Colorado, USA, 2007*, pp. 219-222.

Hemann, C. and Burbary, K. (2013), *Digital Marketing Analytics: Making Sense of Consumer Data in a Digital World*. Pearson Education.

Jansen, B.J., Zhang, M., Sobel, K. and Chowdury, A. (2009), "Twitter power: tweets as electronic word of mouth", *Journal of the American Society for Information Science and Technology*, Vol. 60 No. 11, pp. 2169-2188.

Jurka, T. (2012), "MAXENT: an R package for low-memory multinomial logistic regression with support for semi-automated text classification", *The R Journal*, Vol. 4 No. 1, pp. 56-59.

Kiritchenko, S., Zhu, X. and Mohammad, S.M. (2014). "Sentiment analysis of short informal texts", *Journal of Artificial Intelligence Research*, Vol. 50, pp. 723-762.

Kivran-Swaine, F., Brody, S., Diakopoulos, N. and Naaman, M. (2012), "Of joy and gender: emotional expression in online social networks", in *Proceedings of the Conference on Computer Supported Cooperative Work Companion*, *2012*, ACM, pp. 139-142.

Krippendorff, K. (2012). *Content Analysis: An Introduction to Its Methodology*, Sage.

Lex, A., Gehlenborg, N., Strobelt, H., Vuillemot, R. and Pfister, H. (2014), "UpSet: visualization of intersecting sets", *IEEE Transactions on Visualization and Computer Graphics*, Vol. 20 No. 12, pp. 1983-1992.

Liu, X., Zhang, S., Wei, F. and Zhou, M. (2011), "Recognizing named entities in tweets", in *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1*, Association for Computational Linguistics, pp. 359-367.

Lusch, R.F., Vargo, S.L. and Tanniru, M. (2010), "Service, value networks and learning", *Journal of the Academy of Marketing Science*, Vol. 38 No. 1, pp. 19-31.

Maynard, D. and Greenwood, M.A. (2014), "Who cares about Sarcastic Tweets? Investigating the Impact of Sarcasm on Sentiment Analysis", in *Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC'14),* pp. 4238-4243.

Mohammad, S. M., Zhu, X., Kiritchenko, S., & Martin, J. (2015), "Sentiment, emotion, purpose, and style in electoral tweets", *Information Processing & Management*, Vol. 51 No. 4, pp. 480-499.

Mudinas, A., Zhang, D. and Levene, M. (2012), "Combining lexicon and learning based approaches for concept-level sentiment analysis", in *Proceedings of the First International Workshop on Issues of Sentiment Discovery and Opinion Mining*, ACM.

Murdough, C. (2009), "Social media measurement: It's not impossible", *Journal of Interactive Advertising*, Vol. 10 No 1, pp. 94-99.

Nabi, R.L. (2007), "Emotion and persuasion: A social cognitive perspective", in Roskos-Ewoldsen, D. R., Monahan, J. L. (Ed.) *Communication and Social Cognition. Theories and Methods*, pp. 377-398.

Nabi, R.L. and Oliver, M.B. (2009), *The SAGE Handbook of Media Processes and Effects*. Sage.

Pang, B., Lee, L. and Vaithyanathan, S. (2002), "Thumbs up? Sentiment classification using machine learning techniques", in *Proceedings of the ACL Conference on Empirical Methods in Natural Language Processing-Volume 10, 2002*, Association for Computational Linguistics, pp. 79-86.

Pathak, X., & Pathak-Shelat, M. (2017), "Sentiment analysis of virtual brand communities for effective tribal marketing", *Journal of Research in Interactive Marketing*, Vol. 11 No 1, pp. 16-38.

Pennebaker, J.W., Boyd, R.L., Jordan, K. and Blackburn, K. (2015), *The Development and Psychometric Properties of LIWC2015*, Austin, TX: University of Texas at Austin.

Prabowo, R. and Thelwall, M. (2009), "Sentiment analysis: A combined approach", *Journal of Informetrics*, Vol. 3 No. 2, pp. 143-157.

Rosenthal, S., Nakov, P., Kiritchenko, S., Mohammad, S. M., Ritter, A., & Stoyanov, V. (2015), "Semeval-2015 task 10: Sentiment analysis in twitter", in *Proceedings of the 9th International Workshop on Semantic Evaluation (SemEval 2015)*, pp. 451-463.

Sebastiani, F. (2002), "Machine learning in automated text categorization", *ACM Computing Surveys (CSUR)*, Vol. 34 No. 1, pp. 1-47.

Sommar, F. and Wielondek, M. (2015), *Combining Lexicon-and Learning-based Approaches for Improved Performance and Convenience in Sentiment Classification*, CSC, KTH.

Taboada, M., Brooke, J., Tofiloski, M., Voll, K. and Stede, M. (2011), "Lexicon-based methods for sentiment analysis", *Computational Linguistics,* Vol. 37 No. 2, pp. 267-307.

Tan, S., Wang, Y. and Cheng, X. (2008), "Combining learn-based and lexicon-based techniques for sentiment detection without using labeled examples", in *Proceedings of the 31st Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, 2008,* ACM, pp. 743-744.

Tausczik, Y.R. and Pennebaker, J.W. (2010), "The psychological meaning of words: LIWC and computerized text analysis methods", *Journal of Language and Social Psychology*, Vol. 29 No. 1, pp. 24-54.

Theng So, J., Grant Parsons, A. and Yap, S.F. (2013), "Corporate branding, emotional attachment and brand loyalty: the case of luxury fashion branding", *Journal of Fashion Marketing and Management: An International Journal*, Vol. 17 No. 4, pp. 403-423.

Tirunillai, S. and Tellis, G.J. (2014), "Mining marketing meaning from online chatter: strategic brand analysis of big data using latent dirichlet allocation", *Journal of Marketing Research*, Vol. 51 No. 4, pp. 463-479.

Turney, P.D. (2002), "Thumbs up or thumbs down? Semantic orientation applied to unsupervised classification of reviews", in *Proceedings of the 40th Annual Meeting on Association for Computational Linguistics,* Association for Computational Linguistics, pp. 417-424.

Van Rijsbergen, C. J. (1979), *Information Retrievals*. London: Butterworth.

Wang, W., Chen, L., Thirunarayan, K. and Sheth, A.P. (2012), "Harnessing twitter 'Big Data' for automatic emotion identification. In *Privacy, Security, Risk and Trust (PASSAT), 2012 International Conference on and 2012 International Conference on Social Computing (SocialCom*), IEEE, pp. 587-592.

Appendix C

Paper presented at the Australian and New Zealand Marketing Academy Conference (ANZMAC), 2016

Sentiment analysis for brand-related social media conversations

Chedia Dhaoui, Macquarie University, Australia, chedia.dhaoui@students.mq.edu.au*
LayPeng Tan, Macquarie University, Australia, laypeng.tan@mq.edu.au
Cynthia M. Webster, Macquarie University, Australia, cynthia.webster@mq.edu.au

Abstract

With the wide adoption of social media, and the soaring volumes of brand-related social media conversations, manual approaches to content analysis are no longer practical. Instead, automated computational methods are now required to efficiently analyse the large volume of content data. A recent trend is to classify content according to consumers' feelings and opinions about brands by deploying content analysis techniques for sentiment classification. We argue existing techniques used in academic research and industry practice do not fit the type of data social media provides. This study compares the lexicon-based approach to sentiment analysis with computer supervised learning approach using Facebook data. Results show the two approaches are similar in accuracy but differ substantially in their classification ensembles. To rectify the differences, this study combines the two approaches and demonstrates improved outcomes.

Keywords: social media, marketing analytics, sentiment analysis, big data

Track: Digital Marketing and Social Media

Introduction

The considerable development of social media during the last decade along with the profusion of digital channels, such as social networking sites (e.g., Facebook), microblogs (e.g., Twitter) or media sharing (e.g., Instagram), have revolutionised not only the way brands communicate with their consumers, but also the roles of consumers as they gain an important voice marketers can no longer afford to ignore (Gensler et al., 2013). Social media enables consumers to easily access, co-create and quickly disseminate information, and gain more control over the marketing processes, creating serious dilemmas and challenges for marketers (Constantinides, Romero and Boria, 2009) as well as new opportunities to tap into the unfettered Consumer Generated Content (CGC). Digital marketing is now treated as a “conversation” between businesses and consumers instead of the traditional, one-way business-to-consumers transmissions (Lusch et al., 2010).

A recent trend in the digital marketing analytics sphere is to track and analyse consumers’ feelings and opinions about specific brands, products or services attributed to the CGC on social media (Hemann and Burbary, 2013). The objective is to classify the emotional valence of each CGC, typically text-based, according to some manual or automated classification method. For example, marketers can retrieve timely feedback on a new product by evaluating consumers’ emotions expressed in the comments on a Facebook post or tweets with a specific hashtag related to the product. Sentiment analysis has long been conducted to find the opinions or feelings consumers about products and services using opinion polls, surveys, and focus groups (Liu, 2010). However, using these methods, participants may be unwilling to invoke or revisit emotionally charged memories (Cohen, Pham and Andrade, 2008). Furthermore, the quality of the content relies on the participants’ ability to verbalise their emotions (Cooke and Buckley, 2008). Today, social media platforms are popular vehicles to study consumers on a large scale and in a natural setting (Kivran-Swaine et al., 2012). Researchers focus more on consumers’ comments, reviews and complaints on social media to conduct sentiment analysis because they find them very appealing in terms of consumers’ emotions due to the significant share of online conversations expressing emotions about products and brands (Jansen et al., 2009).

The creation of considerable amounts of social media conversations raises the need to develop automated tools for identifying and analysing people’s emotions expressed in text (Wang et al., 2012). Automated classification of expressed emotions in social media conversations is challenging for several reasons. First, CGC content typically reflects the instant and informal nature of communication on social media (Canhoto and Padmanabhan, 2015). The content typically is free-flowing text, casual in its word and grammar usage (Tirunillai and Tellis, 2014), commonly includes abbreviations, misspellings, emoticons, emojis and often use SMS-like syntax, which current sentiment analysis methods do not adequately support. Additionally, particular platform features, like the 140 character limit for Twitter messages, impede the effectiveness of current automated sentiment analysis tools (Kiritchenko, Zhu, and Mohammad, 2014). Finally, the sheer volume of social media conversations is a significant challenge. Automated technologies turn that challenge into an opportunity by obviating the need for costly and risk-prone manual analysis, instead leveraging computerised procedures to draw insights from social media conversations.

Supported by most automated text classification tools, sentiment analysis can be used by marketers for a rapid, scalable and effective way of gauging consumer’s feelings. However, Canhoto and Padmanabhan (2015) have undertaken a comparative study of automated vs. manual analysis of social media conversations. Their findings show low levels of agreement between manual and automated analysis, which is of “grave concern given the popularity of the latter in consumer research” (Canhoto and Padmanabhan, 2015, p.1141). The fact that manual analysis performs better than the automated one is not surprising. However, it is crucial to further investigate the effectiveness of automated sentiment analysis by taking into account the two main approaches to automated sentiment analysis that exist to date. This is even more crucial to investigate as the evaluating of sentiment analysis tools on social media is challenging (Maynard and Bontcheva, 2016). The lexicon-based approach (Taboada et al., 2010) is the most widely used in the marketing research community. The approach generally relies on a dictionary of opinion words to identify and determine sentiment orientation as positive or negative. The supervised learning approach to sentiment analysis (Pang et al., 2002) is often reported to be more accurate (Chaovalit and Zhou, 2005). By using a fraction of the full data as a manually classified training dataset, the approach trains classifiers to learn by examples, thus "supervising" the classification and without relying on any prior lexicon. As each of these methods has its advantages and limitations, marketers and researchers need to carefully verify the accuracy of the classification (Brown et al., 1990) to avoid acting on inaccurate data analysis outcomes (Canhoto and Padmanabhan, 2015).

The purpose of this paper is to address three questions: 1) Are existing sentiment analysis techniques appropriate for the analysis of social media conversations? 2) To what extent do the results from the two approaches differ? 3) Does a combined approach improve the overall accuracy of the results and how? To answer these questions, we first summarise text classification methods for sentiment analysis used today on social media data. We then outline the research method and empirically evaluate the lexicon-based and supervised learning approaches using a large sample of consumer comments (CGC) on Facebook brand pages. Although results show the two approaches produce relatively similar levels of accuracy for predicting positive and negative sentiment, they produce quite different ensembles of positive and negative comments. We then demonstrate that combining the two approaches leads to better results both in terms of precision and recall of the sentiment analysis.

Sentiment analysis: a text classification problem

Text categorisation techniques are used to classify any text-based document into predefined categories reflecting the valence, emotions or topics referred to in the text. Both lexicon-based method and supervised learning approaches to sentiment analysis typically classify any given text into positive or negative sentiment according to the polarity of the content. The lexicon-based approach uses emotion words often compiled into a sentiment lexicon, also known as a sentiment dictionary. A standard lexicon like the Linguistic Inquiry and Word Count (LIWC) includes such a sentiment dictionary. While different bodies of sentiment lexicon can be created for specific subject matters, sentimental words included in most lexicon-based sentiment analysis tools are not specific to a particular topic (Godbole, Srinivasaiah and Steven, 2007). Furthermore, misspellings, colloquialisms, foreign words, and abbreviations are usually not included in the used lexicon.

Since building lexicon-based text classifiers by hand is difficult and time-consuming, it is advantageous to use supervised learning methods that employ training datasets for automating data classification. The supervised learning approach typically trains sentiment classifiers using features such as unigrams or bigrams (Pang et al. 2002) by applying different learning techniques such as Naive Bayes, Maximum Entropy or Support Vector Machines. These methods need manual labelling of training examples which can be time consuming. However, limiting the size of the training dataset leads to poorer classification accuracy. The choice of which approach to use is crucial as it impacts the accuracy of the sentiment classification and should be carefully aligned with the type of data being analysed. Most studies, however, adopt a particular approach for its convenience and ease of use with few questioning whether the sentiment classification approach is appropriate and actually "fits" the data.

Research Method

Data collection and sampling

Luxury fashion brands were considered an appropriate context for the study given the emotional value consumers attach to the fashion industry (Theng, Grant and Yap, 2013). The Fashion 2015 Digital IQ Index® from L2 Inc was used to select a sample of 83 luxury fashion brands highly active on Facebook social media platform. Facebook Graph API was used to collect all posts published and their associated CGC (comments) on the selected brands' Facebook brand pages over a 9 month period. From the initial data collected, the most relevant comments for each post, also called "top comment", were identified using the comment ranking algorithm introduced by Facebook back in 2012. The choice of top comments is crucial as it reflects not only the most meaningful comments but also the most viewed comments. Indeed, top comments are always visible under a post which means top comments are the most likely to have an impact on other consumers, and thus play a role in stimulating emotion laden brand conversations and the most likely to require content analysis for marketers to gain insights into consumers' feelings, thoughts and opinions.

Supervised learning method for sentiment analysis

RTextTools is a machine learning package in R for automatic text classification. The package includes several algorithms for ensemble classification including maximum entropy, random forests, SVM, bagging, decision tree, etc. We tested the different algorithms and chose the best performing ones: Maximum Entropy Modelling for predicting positive sentiment and the Bagging method for predicting negative sentiment. Maximum Entropy Modeling (Maxent), uses a low-memory multinomial logistic regression with support for semi-automated text classification (Jurka, 2012). Bagging (Breiman, 1996) is a "bootstrap" (Efron and Tibshirani, 1993) ensemble method used to train each classifier using a random redistribution of the training dataset.

A manually classified dataset included 850 top comments, half of which was used as a training dataset and the other half reserved as a testing dataset. The training dataset was fed into the Maxent and Bagging supervised learning algorithms to train and test two classifiers, one for positive sentiment and one for negative sentiment. Each distinct word, emoji or emoticon corresponds to a feature, with the number of times a feature occurs in the document as its value. The resulting representation scheme, generated by the RTextTools package in R, is a term matrix of 221 terms from the training dataset such as "cute", "elegant", "horrible", etc., but also emojis and emoticons. Each of the trained classifiers uses a subset of those terms, automatically selected and weighted by the Maxent or the Bagging algorithms.

Lexicon-based approach to sentiment analysis

To assess the sentiment expressed in CGC content automatically without requiring manual classification of a training dataset, we used LIWC2015 (Pennebaker et al. 2015), a text analysis software that calculates the degree of use for various categories of words in text-based documents. Among those categories, LIWC supports a sentiment lexicon for positive and negative emotions. LIWC has been widely used in psychology and linguistics (Tausczik and Pennebaker, 2010). For each emotion polarity the software calculates the relative frequency with which words related to that polarity occur in a given text sample (e.g., the words "love", "nice", or "sweet" are counted as representatives of positive emotion, while the words "hurt", "ugly", "nasty" are counted as representatives of negative emotion).

Analytics

The reserved testing dataset was used to test the two approaches of text analysis for sentiment classification and compare their results. To measure performance, the standard evaluation measures of precision (p), recall (r) and F-score (F), $F = 2\ p\ r\ /\ (p+r)$. The F-score combines recall with precision, and is used as a single performance indicator that is high if both p and r are high and low if either p or r are low.

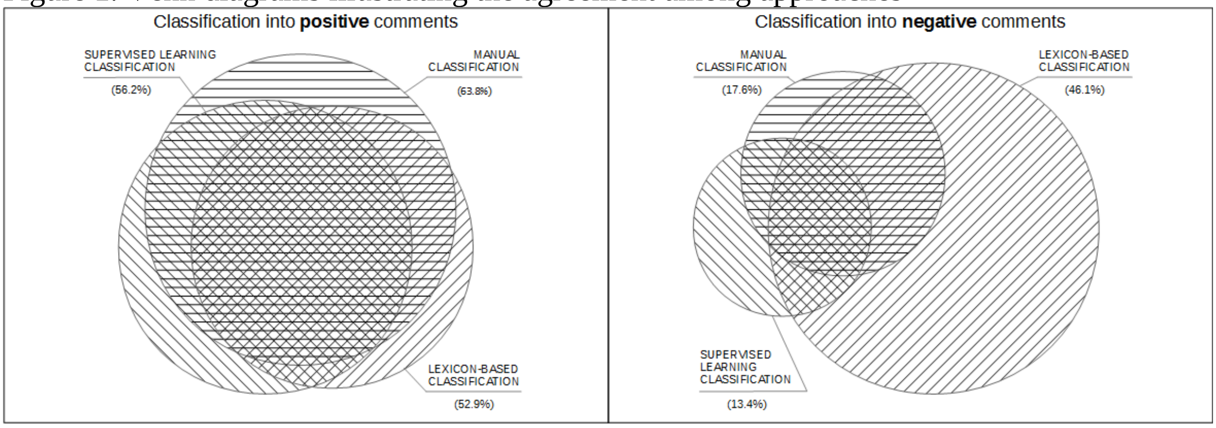
Findings

Table 1 summarises the performance results of the classification models. While supervised learning classification methods are claimed to be more accurate (Chaovalit and Zhou, 2005), the results show that, when aiming at maximising accuracy (highest F-score), both approaches to sentiment analysis perform similarly, though both are more accurate at classifying positive sentiment than negative. The low level of accuracy in classifying negative sentiment, below 0.5, is explained by the well-recognised limitations of automated sentiment analysis when it comes to analysing sarcasm, which is often a limitation for manual approaches too (Maynard and Greenwood, 2014). Therefore, the existing sentiment analysis techniques are appropriate for predicting positive sentiment, and limited for predicting negative sentiment, from the analysis of social media conversations.

Table 1. Comparison of comment sentiment classification approaches

	Positive sentiment				Negative sentiment			
	%	p	R	F	%	p	r	F
Manual classification	63.8%	1	1	1	17.6%	1	1	1
Lexicon-based approach	52.9%	0.85	0.71	0.77	46.1%	0.31	0.81	0.45
Supervised learning approach	56.2%	0.83	0.73	0.78	13.4%	0.54	0.41	0.47
Combined approaches	71.1%	0.79	0.88	0.83	52.2%	0.31	0.91	0.46

Figure 1. Venn diagrams illustrating the agreement among approaches



By matching manually classified comments and the automated classifications outcome, the lexicon-based and the supervised learning approaches agree on 63.6% of correctly classified positive comments and 35.3% of correctly classified negative comments, as illustrated in the Venn diagrams of Figure 1. This indicates that one approach is complementing the other and that a combination of the approaches may produce a better outcome. Given the apparent complementarity of the ensembles produced by the two approaches, a combination of the results would be a sensible way of improving the results. Table 1 shows the results of the combined approaches in which the union of the ensembles are considered. The F-score for classifying positive sentiment increased substantially, scoring 83% accuracy, but accuracy in classifying negative sentiment stayed relatively the same when using a combined approach. This indicates that, by combining the two approaches, the overall performance of sentiment classification is greatly improved for classifying positive sentiment. Furthermore, the combined approach has the merit of being simple to implement using existing tools, and combining their results.

Conclusions and implications for future research

Among the variety of data analysis methods and techniques, the use of sentiment analysis for gauging public opinion is widely adopted by companies and researchers. Marketers apply these methods without evaluating their effectiveness at classifying the emotional valence of certain social media data sources, such as conversational data in the form of comments or tweets. In this paper, we have investigated the fit between the two main sentiment analysis approaches, as well as their combination, using conversational social media data consisting of Facebook comments. To extend our study results, the combined approach needs to be applied to other kind of conversational data such as tweets and microblogs and empirically explore the potential differences in performance of sentiment analysis approaches across social media platforms. Although the fields of natural language processing, computational linguistics, and text analytics continue to mature, they arguably remain unable to match the ability of humans to take subtle aspects of the context into account and make fine distinctions when interpreting the content data (Conway, 2006) as empirically verified in this paper by the relatively low levels of accuracy for negative sentiments. For these reasons, further research is required to guide marketers on how to select and match the various text analysis approaches with the different social media data sources to generate precise and accurate outcomes.

References

Breiman, L. (1996). Bagging predictors. *Machine learning*, 24(2), 123-140.

Brown, D., Taylor, C., Baldy, R., Edwards, G., & Oppenheimer, E. (1990). Computers and QDA-can they help it? A report on a qualitative data analysis programme. *The Sociological Review*, 38(1), 134-150.

Canhoto, A. I., & Padmanabhan, Y. (2015). 'We (don't) know how you feel'–a comparative study of automated vs. manual analysis of social media conversations. *Journal of Marketing Management*, 31(9-10), 1141-1157.

Chaovalit, P., & Zhou, L. (2005). Movie review mining: A comparison between supervised and unsupervised classification approaches. In *Proceedings of the 38th Annual Hawaii International Conference on System Sciences* (pp. 112c-112c). IEEE.

Cohen, J. B., Pham, M. T., & Andrade, E. B. (2008). The nature and role of affect in consumer behavior. In Curtis P. Haugtvedt, Paul Herr, Frank Kardes (Ed.), *Handbook of Consumer Psychology* (pp. 297-348). Erlbaum.

Constantinides, E., Romero, C. L., & Boria, M. A. G. (2008). Social media: a new frontier for retailers? In *European Retail Research* (pp. 1-28). Gabler Verlag.

Conway, M. (2006). The subjective precision of computers: A methodological comparison with human coding in content analysis. *Journalism & Mass Communication Quarterly*, 83(1), 186-200.

Cooke, M., & Buckley, N. (2008). Web 2.0, social networks and the future of market research. *International Journal of Market Research*, 50(2), 267.

Efron, B., & Tibshirani, R. J. (1994). *An introduction to the bootstrap*. CRC press.

Gensler, S., Völckner, F., Liu-Thompkins, Y., & Wiertz, C. (2013). Managing brands in the social media environment. *Journal of Interactive Marketing*, 27(4), 242-256.

Godbole, N., Srinivasaiah, M., & Skiena, S. (2007). Large-Scale Sentiment Analysis for News and Blogs. In Proceedings of the First International Conference on Weblogs and Social Media (pp. 219-222) , Boulder, Colorado, USA.

Hemann, C., & Burbary, K. (2013). *Digital marketing analytics: making sense of consumer data in a digital world*. Pearson Education.

Jansen, B. J., Zhang, M., Sobel, K., & Chowdury, A. (2009). Twitter power: Tweets as electronic word of mouth. *Journal of the American society for information science and technology*, 60(11), 2169-2188.

Jurka, T. P. (2012). MAXENT: An R package for low-memory multinomial logistic regression with support for semi-automated text classification. *The R Journal*, 4(1), 56-59.

Kiritchenko, S., Zhu, X., & Mohammad, S. M. (2014). Sentiment analysis of short informal texts. *Journal of Artificial Intelligence Research*, 50, 723-762.

Kivran-Swaine, F., Brody, S., Diakopoulos, N., & Naaman, M. (2012, February). Of joy and gender: emotional expression in online social networks. In *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work Companion* (pp. 139-142). ACM.

Liu, B. (2010). Sentiment Analysis and Subjectivity. *Handbook of natural language processing*, 2, 627-666.

Lusch, R. F., Vargo, S. L., & Tanniru, M. (2010). Service, value networks and learning. *Journal of the Academy of Marketing Science*, 38(1), 19-31.

Maynard, D. G., & Bontcheva, K. (2016). Challenges of Evaluating Sentiment Analysis Tools on Social Media. Proceedings of LREC 2016.

Maynard, D., & Greenwood, M. A. (2014, May). Who cares about Sarcastic Tweets? Investigating the Impact of Sarcasm on Sentiment Analysis. In *Proceedings of the Language Resources and Evaluation Conference* (pp. 4238-4243). Reykjavik, Iceland.

Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and trends in information retrieval*, 2(1-2), 1-135.

Pennebaker, J.W., Boyd, R.L., Jordan, K., & Blackburn, K. (2015). The development and psychometric properties of LIWC2015. *Austin, TX: University of Texas at Austin*.

Taboada, M., Brooke, J., Tofiloski, M., Voll, K., & Stede, M. (2011). Lexicon-based methods for sentiment analysis. *Computational linguistics*, 37(2), 267-307.

Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology*, 29(1), 24-54.

Theng So, J., Grant Parsons, A., & Yap, S. F. (2013). Corporate branding, emotional attachment and brand loyalty: the case of luxury fashion branding. *Journal of Fashion Marketing and Management: An International Journal*, 17(4), 403-423.

Tirunillai, S., & Tellis, G. J. (2014). Mining marketing meaning from online chatter: Strategic brand analysis of big data using latent dirichlet allocation. *Journal of Marketing Research*, 51(4), 463-479.

Wang, W., Chen, L., Thirunarayan, K., & Sheth, A. P. (2012, September). Harnessing twitter" big data" for automatic emotion identification. In *Proceedings of the International Conference on Social Computing* (pp. 587-592). Amsterdam, The Netherlands. IEEE.

Appendix D

Paper presented at the 6th Global Innovation and Knowledge Academy, 2017

Emotional dynamics in social media

Chedia Dhaoui, Cynthia M. Webster, Lay Peng Tan

Macquarie University, Sydney, Australia

Abstract

This paper investigates the emotional dynamics in social media by examining brand-generated posts and responding consumer comments. The results of an empirical study of 166 Facebook brand pages suggest that emotional content in brand-generated posts increases emotional contagion to the consumers. Furthermore, positive emotional content and high arousal emotional content in brand-generated posts lead to greater emotional contagion compared, respectively, to negative emotional content and low arousal emotional content. Results also show that visual emotional content in brand-generated posts contributes to greater emotional contagion compared to verbal emotional content. Finally, this paper reveals that consumer-generated emotional comments lead to greater emotional contagion compared to brand-generated emotional posts, empirically supporting previous research on brand communication. These results further our understanding of how emotional branding and emotional contagion operate within brand community members on digital social media.

Keywords: emotional dynamics, emotional contagion, online branding, social media

INTRODUCTION

Today social media is an integral part of online branding. A great deal of social media marketing content is emotionally loaded to better connect with consumers and influence their perceptions, thoughts and feelings towards the brand - the so-called emotional branding. Emotional branding refers to the engagement of consumers in a deep, long-term, intimate connection with the brand (Morrison and Crane, 2007). The emotional branding perspective suggests that firms ought to concentrate on forging strong and meaningful emotional bonds that proactively enrich consumers' lives, become part of their memories and social networks (Thompson et al. 2006). As a response to emotional branding, consumers praise or complain about the brand, behaviors strongly shaped by emotions. Such responses, in turn, affect other consumers' engagement and feelings towards the brand thanks to the virality of social media.

This paper investigates the emotional dynamics on Facebook brand pages, focusing on two facets of emotional branding, namely: emotional engagement as consumers' responses to brand generated emotional content, and emotional contagion as consumers' responses to other consumers' emotional content. The aims of this research are to examine: 1) the extent to which Facebook brand pages make use of verbal and visual emotional content, 2) the impact of emotional brand-generated content on consumers' engagement and feelings towards the brand and 3) how emotional consumer-generated content influences other consumers' engagement and feelings towards the brand via an emotional contagion phenomenon.

This study examines a combination of verbal and visual data collected from 166 Facebook brand pages. Verbal data consist of text based brand-generated posts, as well as all consumer comments and replies to comments. Visual data consist of photos and videos posts. Automated sentiment analysis is used to classify the verbal text component for the six emotions of anger, fear, disgust, sadness, surprise and joy. The six emotions are then mapped into two dimensions of valence, positive versus negative, and arousal, high versus low, using Russel's (1980) Circumplex Model of Affect. As automated text mining techniques do not analyze the emotional content of photos and videos, qualitative research is required to identify the emotional states expressed in visual data. Using Borth et al.'s (2013) Visual Sentiment Ontology, which draws from Plutchik's (1997) Wheel of Emotions, a 10% random sample of the data (580 photos and 183 videos) are manually tagged using Adjective Noun Pairs (ANP) from the Visual Sentiment Ontology (Borth et al., 2013). The twenty three different emotions of Plutchik's (1997) Wheel of Emotions are then quantified for every post based on its associated ANPs and mapped into the two dimensions of valence and arousal using Russel's (1980) Circumplex Model of Affect.

The findings reveal that only a small proportion of brand posts use text form, which means the overwhelming majority of emotional posts are visual in the form of photos or videos which require human intervention. This highlights the limitation of focusing sentiment analysis on verbal data and the importance of incorporating qualitative techniques to examine visual data when dealing with social media content. Results also show brand-generated emotional content appears to have less influence on consumers' online emotional responses than consumer-generated emotional content, suggesting consumer-to-consumer emotional contagion is more influential than firms' attempts at emotional branding.

BACKGROUND

Emotions and Word-of-Mouth Communications

Emotions are "intense, relatively short-term affective reactions to a specific environmental stimulus" (Reber, 1995). Consumers engage emotionally with brands for a variety of reasons. Branding research shows that consumers' emotions toward a brand are associated with their satisfaction and loyalty (Morrison and Crane, 2007) as well as several other behavioral responses (Heath et al., 2006; Ruth, 2001; Thompson et al., 2006; Tsai, 2005) including word-of-mouth (WOM) communication (Kim and Gupta, 2012; Ladhari, 2007). Advertising research confirms emotions have a positive effect on engagement (Teixeira, Wedel, and Pieters, 2010) and virality (Berger and Milkmann, 2012, Eckler and Bolls, 2011). Indeed consumer emotions can result from exposure to marketing content and such feelings can occur quite quickly especially if activated by visual elements of the ad (Edell 1987; Zajonc 1980). Furthermore, consumption emotions are significant predictors of complaining behavior and word-of-mouth (WOM) transmission (Westbrook, 1987). Ferrara and Yang (2015) empirically demonstrate a linear relationship between the average emotional valence of the stimuli users are exposed to on twitter, and that of the responses they produce.

Studies find satisfied consumers engage in positive WOM as a response to fulfillment of their needs and desires (Heckman and Guskey, 1998; Mittal et al., 1999; Oliver 1997). Chitturi et al. (2008) provide empirical evidence that high arousal emotions, such as delight, lead to more positive word of mouth though not all studies find a direct relationship between satisfaction and WOM (Arnett et al., 2003; Bettencourt, 1997; Reynolds and Beatty, 1999). Consumers also engage in negative WOM. According to Thogersen et al. (2009) and Verhagen et al. (2013), consumers use negative electronic WOM (eWOM) to convey their dissatisfaction about products and seek solutions or compensation for bad experiences. Negative eWOM can also be for altruistic reasons, consumers disclosing their negative experiences to prevent others from suffering similar incidents (Litvin et al., 2008), and can be constructive, such as complaining to make sure a problem is solved (Zaugg & Jaggi, 2006). Conversely, negative eWOM can be quite destructive with some consumers, known as trolls, sharing “inflammatory, extraneous or off-topic messages […] in social media, with the primary intent of provoking readers into an emotional response or of otherwise disrupting normal on-topic discussion” (Noble et al., 2012, p.477).

Emotional branding on social media

On social media, brand marketers post emotionally loaded marketing content with positive, neutral, or negative valence that can impact on consumers’ feelings towards the brand. According to Berger and Milkman (2012), emotional content is more likely to capture public attention with “positive content more viral than negative content, but the relationship between emotion and social transmission is more complex than valence alone” (p.10). Emotionally evocative content can assist consumers in developing strong and deep feelings towards brands as arousing content triggers feelings like surprise, anger, fear, disgust, sadness or joy (Strapparava and Valitutti 2004). Ultimately, companies use Facebook brand pages in the hope that consumers will engage emotionally with the brand generated content by “liking” it, “sharing” it with wider Facebook users, or “commenting” on the content and influencing others by means of emotional contagion, thus contributing to the emotional dynamics happening within and beyond the brand community in online social networks. The success of emotional branding lies in understanding why consumers express positive and negative emotions about brands.

Emotional contagion

Emotions can spread among individuals in a process of emotional contagion (Hatfield, Cacioppo, & Rapson, 1994) which involves the convergence of one's emotional state with the emotional states of those with whom one is observing or interacting (Hatfield, Cacioppo, & Rapson, 1994). Emotional contagion is considered as a type of social influence (Schachter, 1959; Cacioppo and Petty, 1987; Levy and Nail, 1993) which occurs at both subconscious and conscious levels (Druckman and Bjork, 1994; Totterdell, 2000; Kelly and Barsade, 2001) where one actor's emotional display can influence the emotions, thoughts, and behavior of other actors, and where this influenced emotional reaction can, in turn, impact a third party (Scarduzio & Tracy, 2015) involving multiple people in a cycle of reciprocal influence (Hareli & Rafaeli, 2008)

Much of the early research on emotional contagion focuses on moods, weaker more diffuse affective reactions (Tellegen, 1985), and nonverbal expressions of emotional states. This tendency stems from the idea that nonverbal cues, such as facial expressions (Dimberg, 1982), body language (Bernieri, 1988; Chartand and Bargh, 1999), speech patterns (Ekman, Fiesen and Scherer, 1972) and vocal tones (Hietanen, Surakka, and Linnankoski, 1998; Neumann and Strack, 2000) are "necessary" for emotional contagion (Barsade, 2002; Ekman, 1992). Therefore, emotional contagion occurs trough automatic, continuous, synchronous, primitive processes through nonverbal mimicry and feedback (Hatfield, Cacioppo, and Rapson, 1994).

Since the proliferation of digital social media, recent papers indicate that emotions can also be contracted through computer-mediated communication (CMC) systems (Guillory et al., 2011; Hancock et al., 2008) similarly to traditional emotional contagion observed during in-person interactions (Hatfield, Cacioppo & Rapson, 1992; 1993). In particular, the spread of emotions via Facebook has been studied. In a large scale study Kramer, Guillory and Hancock (2014) find that when users of a social media platform make a status update with emotional content on their profile, their friends are more likely to make generate a valence-consistent emotional content. Guadagno et al.'s (2013) study of emotional contagion inherent to video sharing on social networks confirms that only content generating strong affective responses are likely to spread as a viral video. Results of these studies may contain some bias due to the fact that friends or acquaintances may be more likely to share positively-valenced information among themselves (Peters & Kashima, 2007).

RESEARCH HYPOTHESES

To date, no study has examined emotional contagion on social media within the context of branding. This paper fills this gap by investigating whether and how emotional contagion operates among brand community members on Facebook brand pages. Based on previous research discussed, the following five hypotheses are proposed:

Hypothesis 1: Emotional content in brand-generated posts increases emotional contagion from the brand to the consumer generated comments.

Hypothesis 2: Positive emotional content in brand-generated posts leads to greater emotional contagion compared to negative emotional content in brand-generated posts.

Hypothesis 3: High arousal emotional content in brand-generated posts leads to greater emotional contagion compared to low arousal emotional content in brand-generated posts.

Hypothesis 4: Visual emotional content in brand-generated posts leads to greater emotional contagion compared to verbal emotional content in brand-generated posts.

Hypothesis 5: Consumer-generated emotional comments lead to greater emotional contagion compared to brand-generated emotional posts.

METHOD

Since social media includes both verbal and visual data, a mixed method approach combining quantitative and qualitative analytic techniques is required to test the proposed hypotheses. First, the social media data collection and sampling processes are outlined. A general discussion of emotion classification follows with details provided for the quantitative, automated sentiment analysis applied to the verbal data and the qualitative, tagging approach used for the visual data.

Data Collection

Using Facebook's Fan Page List directory (Fan Page List 2015), an initial sample of 200 "most talked about" Facebook brand pages was selected. A manual verification process involved visiting each of the 200 listed Facebook brand pages, eliminating duplicates and removing non-English writing pages. As a result, a total of 166 out of the initial 200 Facebook brand pages were considered for the remainder of the study. The corresponding brands span across six industry sectors including automotive, entertainment, gaming, retail and technology. Over a three month period, from 1st June to 31st August 2015, 7750 posts, their associated 2,159,780 comments, and 1,639,345 consumer replies to comments were collected which included both verbal and visual data. Verbal data consisted of text based brand-generated posts, all consumer comments to posts and all replies to comments. Visual data consisted of photos and videos posts.

Classifying Emotions

In this study, verbal and visual data had to be classified into specific emotions to allow further analysis of emotional dynamics. Two basic approaches to emotion research exists: models of discrete emotions and dimensional models. Theories of discrete emotions typically identify between six and twelve independent monopolar factors of affect, such as sadness, anger, disgust, fear, happiness, surprise (e.g., Ekman, 1992; Izard, 1972). The discrete approach treats each emotion separately and does not provide a framework to estimate how similar or different emotions are to one another. As such, this research takes a dimensional approach which considers emotions to be adequately represented with only two bipolar dimensions of valence and arousal. Russel's (1980) Circumplex Model of Affect (CMA) used the two dimensions of valence and arousal to characterize 28 affect words and empirically quantify their respective valence and arousal levels. Placed in a circular arrangement, eight affect concepts were defined: pleasure, excitement, arousal, distress, displeasure, depression, sleepiness and relaxation, which are used in this study. Plutchik's (1997) Wheel of Emotions (WOE) also follows a circular ordering with the following eight emotion words: joy, anticipation, anger, disgust, sadness, surprise, fear and trust. Some similarities exist between the CMA and the WOE but there are also notable differences. However, the key benefit of adopting a dimensional approach is to map specific emotions into valence and arousal coordinates and vice versa, allowing to easily switch from one representation of emotions to another.

Emotions contained within verbal data can be classified using quantitative, automated techniques. For the current study the R "sentiment" package (R Core Team, 2013) was used with the emotion classifier trained on Strapparava and Valitutti's (2004) emotions lexicon comprising six emotions, namely: anger, fear, disgust, sadness, surprise and joy. The emotion classification from the automated sentiment analysis can then be mapped into the affect concepts of the CMA (Russel, 1980) respectively as arousal, distress, displeasure, depression, excitement and pleasure.

At this stage, automated text mining techniques do not analyze the emotional content of visual data. As such, qualitative research is crucial to identify the emotional states expressed in photos and videos. Borth et al.'s (2013) Visual Sentiment Ontology (VSO) is based on the Plutchik's WOE and is one of the few frameworks for sentiment analysis on visual content. The VSO consists of 1172 adjective noun pairs (ANP) and their associated sentiments among 23 different emotions. The ANPs used in the VSO provide a mid-level representation of sentiment resulting from images acquired from Flickr, and a benchmark containing hundreds of photo tweets covering a diverse set of topics. By mapping the 23 different emotions of the VSO into the 28 affect words of Russel's (1980) CMA, valence and arousal levels can be derived which can then be used to estimate the occurrences of the eight affect concepts of the CMA within the visual content. Each post would potentially express multiple emotions, and the ANP tags would help quantify the intensity of those emotions in terms of valence and arousal as the radius in the CMA representation.

Due to the large number of posts (7750) collected, a qualitative study on the full dataset was not practicable. Therefore, a 10% random sample of the data was selected, totaling 865 posts, (102 text, 580 photos and 183 videos), and were considered for the remainder of the study. Verbal data were subjected to automated sentiment analysis. Visual data first were manually tagged using up to 5 ANPs, each based on the dominant visual elements. One researcher tagged each of the 763 visual posts and calculated their scores for each of the 23 emotions supported by VSO, which were then mapped into the eight affect concepts of the CMA as described earlier. A sub-sample of 100 posts were re-tagged by a research assistant to verify the reliability of the tagging process. The resulting mapping concur for each of the eight affect concepts of the CMS including pleasure (86.5%), excitement (100%), arousal (98.9%), distress (98.9%), displeasure (85.4%), depression (98.9%), sleepiness (58.4%) and relaxation (94.4%). On average, there is 90.2% agreement among taggers on the mapping into the eight affect concepts of the CMA.

The results of automated sentiment analysis of verbal data and the manual tagging of visual data allowed to map brand generated posts and consumers' comments and replies to comments into the eight affect concepts of the CMA (Russel, 1980). The final dataset consists of the eight scores (one for each CMA affect concepts) for each of the 865 posts along with the proportion of comments and replies to comments in each of the eight CMA affect concepts.

RESULTS

Findings reveal that a very small proportion of posts, only 1.3%, are in text form. This highlights the limitation of focusing sentiment analysis on verbal data using automated techniques and the importance of examining visual data when dealing with social media data. The remaining posts, 74.9% photos and 23.7% videos, require qualitative analytic techniques. The automated emotion classification of verbal data found that 53 out of 102 verbal posts, 121,876 out of 2,159,780 comments collected for this study, and 32,522 out of 1,639,345 replies to comments were found to evoke emotions. The 10% sample of posts generated 79,326 comments, among which 15,104 were found to evoke emotions.

Figure 1 illustrates the distribution of the 865 brand posts considered for analysis by type of post and emotion classification. Clearly most emotional content in brand-generated posts are visual, positive and arousing.

Relatively few brand generated emotional posts convey negative valence. Figure 1 (right) shows the distribution of dominant emotions in visual and verbal posts.

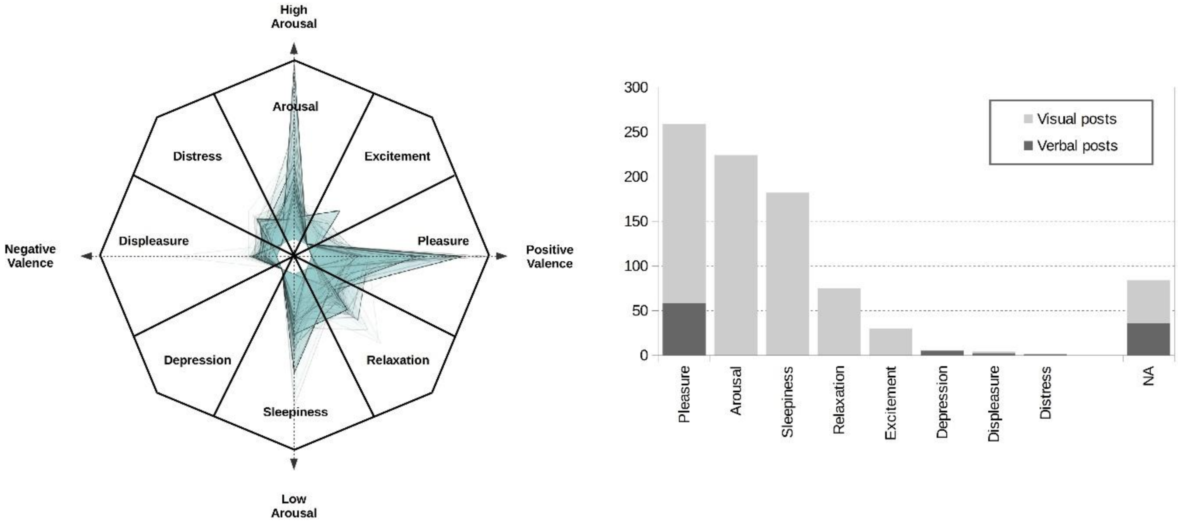


Figure. 1. Distribution of visual posts in the two dimensional space of valence and arousal, and distribution of posts across eight affects.

We first investigate whether or not emotional content in brand-generated posts increases emotional contagion to consumers. To do that, a Pearson's correlation was run to determine the relationship between the eight affect scores of brand generated posts and the proportions of consumers' comments expressing the eight affects considered. The results are reported in Table 1.

Table 1. Correlation table between posts' affect scores and comments' affect proportions

		Post's affect scores							
		Pleasure	Excitement	Arousal	Distress	Displeasure	Depression	Sleepiness	Relaxation
Comments' affect proportions	Pleasure	0.13***	0.04	-0.05	0	-0.05	-0.04	0.04	-0.10*
	Excitement	-0.10**	0.01	0.10**	0	0.20***	-0.02	0	0.07
	Arousal	-0.08*	-0.02	0.02	0	-0.04	-0.04	0.03	0.04
	Distress	-0.02	-0.04	0.01	0.09*	-0.04	0	-0.10*	-0.04
	Displeasure	-0.01	0.01	0.03	-0.05	0.02	-0.02	-0.04	0.08
	Depression	-0.06	-0.04	-0.01	0.05	0	0.15***	0.03	0.06

The results indicate a significant and positive correlation between several of the post's affect scores and the proportions of comments expressing the same affect. In particular, posts expressing pleasure (r= 0.13, N=864, p<0.001), distress (r=0.09, N=864, p<0.05), and depression (r=0.15, N=864, p<0.001) have been found to be positively correlated with their counterparts in consumers' comments, supporting Hypothesis 1.

However, hypothesis 1 is not supported for posts evoking displeasure (negative valence). Indeed, posts expressing displeasure have been found to be positively correlated with the proportion of consumers' comments evoking excitement (high arousal), phenomenon contrary to emotional contagion. This result shows that negative emotions in brand posts leads to less emotional contagion, supporting Hypothesis 2.

Interestingly, the proportion of consumers' comments expressing excitement is positively correlated with the post's arousal score ($r=0.10$, $N=864$, $p<0.01$). Given the relative proximity of arousal and excitement affects in the CMA (Russel, 1980), this correlation is consistent with the emotional contagion phenomenon. In addition, the significant negative correlation of the proportion of consumers' comments expressing sleepiness or relaxation (both being low arousal affects) with the post's distress and pleasure scores (both higher arousal affects) is a contrary effect to emotional contagion phenomenon, creating feelings and emotions opposite to the ones expressed in brand content. These results support Hypothesis 3.

Fisher r-to-z transformation is used to test the significance of the differences between two Pearson's correlation coefficients. It is used in this study to test the interaction effects of the type of post (visual vs verbal) on emotional contagion, allowing to test hypotheses 4. The results of Fisher r-to-z transformation are reported in Table 2 where only significant z values are listed. The resulting value of z will have a positive sign if the correlation in the second group is significantly greater than in the first group, and negative otherwise. The results show stronger correlation between opposite affects in verbal posts (displeasure posts and excitement comments) leading to less emotional contagion in verbal posts, supporting Hypothesis 4.

Table 2. Results of Fisher r-to-z transformation comparing the Pearson's correlation matrices of independent groups based on post type (only significant z values are reported).

	Correlations compared	**Z**
Verbal vs Visual	Comparison of correlation coefficients of post's **distress** score and proportion of **distress** comments in **verbal vs visual posts**.	8.69***
	Comparison of correlation coefficients of post's **displeasure** score and proportion of **excitement** comments in **verbal vs visual posts**.	4.81***

Finally, to test Hypothesis 5, the focus is shifted from the effect of brand generated emotional content on consumers' emotional content, to the effect of consumers on each other's. In particular, we examine how the emotions evoked in consumer's comments affect the emotions expressed in consumers' responses to the comments. A Pearson's correlation was run to determine the relationship between the affect of consumers' comments and the proportions of consumers' replies to the comments expressing the eight affects. The results are reported in Table 3 including the Pearson correlation coefficients and their statistical significance tests.

Table 3. Correlation table between posts' affect scores and comments' affect proportions

		Comment's affect					
		Pleasure	Excitement	Arousal	Distress	Displeasure	Depression
Replies' affect proportions	Pleasure	0.12***	-0.05*	-0.05*	-0.05*	0.01	-0.04
	Excitement	-0.06*	0.07**	0	0	0.02	-0.02
	Arousal	-0.05*	0.03	0.15***	0	0	-0.02
	Distress	-0.02	-0.04	-0.04	0.06*	-0.02	0.02
	Displeasure	-0.04	-0.01	0	0.01	0.02	-0.03
	Depression	-0.04	0.01	-0.04	0.02	-0.02	0.07***

The results indicate that there is a significant and positive correlation between most of the comments' affect scores and the proportions of consumers' replies expressing the same affect. Furthermore, there is are several significant negative correlations between opposite emotions, further contributing to focalizing the replies' emotions on the same affect. Thus, these results strongly support Hypothesis 5.

CONCLUSIONS

This paper contributes to the research and practice of emotional branding by improving the understanding of the dynamics of emotions expressed and shared on Facebook brand pages. The results of an empirical study of 166 Facebook brand pages suggest that emotional content in brand-generated posts increases emotional contagion. Furthermore, findings show that positive content and high arousal content in brand-generated posts lead to greater emotional contagion compared, respectively, to negative content and low arousal content. Visual emotional content in brand-generated posts was found to lead to greater emotional contagion compared to verbal emotional content. These results support previous findings based on the idea that nonverbal cues are "necessary" for emotional contagion (Barsade, 2002; Ekman, 1992) and that emotions can be contracted through computer-mediated communication systems (Guillory et al., 2011; Hancock et al., 2008) and lead to emotional contagion on digital social media.

Consumer-generated emotional comments were also found to lead to greater emotional contagion compared to brand-generated emotional posts. This finding empirically supports previous research on brand communication (Christodoulides et al., 2011) considering that User Generated Content provides tangible evidence that the power asymmetry between consumers and organizations is reversing in favor of consumers.

Like any research, this work has its limitations which serve as avenues for further research. First, we used a sample of "most talked about" Facebook brand pages. Instead, sampling could be done within the population of posts rather than the population of brands to provide greater control of the sampling process. Second, in order to improve the validity of sentiment analysis, machine learning algorithms could be used and trained with data obtained from qualitative human classification. This would be an even tighter combination of qualitative and quantitative methods. Further analysis of the interaction effect of brand replies to consumers' comments would fill a gap in the literature as pointed out by Gotthilf (2010) who suggested that companies should leverage the two-way conversations enabled by social media platforms. Providing empirical evidence of the effect of brand replies on emotional contagion would help deepen our understanding of emotional dynamics in brand-related social media conversations.

References

Arnett, D. B., German, S. D., & Hunt, S. D. (2003). The identity salience model of relationship marketing success: The case of nonprofit marketing. Journal of marketing, 67(2), 89-105.

Barsade, S. G. (2002). The ripple effect: Emotional contagion and its influence on group behavior. Administrative Science Quarterly, 47(4), 644-675.

Berger, J., & Milkman, K. L. (2012). What makes online content viral?. Journal of marketing research, 49(2), 192-205.

Bernieri, F. J., Reznick, J. S., & Rosenthal, R. (1988). Synchrony, pseudosynchrony, and dissynchrony: measuring the entrainment process in mother-infant interactions. Journal of personality and social psychology, 54(2), 243.

Bettencourt, L. A. (1997). Customer voluntary performance: customers as partners in service delivery. Journal of retailing, 73(3), 383-406.

Borth, D., Ji, R., Chen, T., Breuel, T., & Chang, S. F. (2013). Large-scale visual sentiment ontology and detectors using adjective noun pairs. In Proceedings of the 21st ACM international conference on Multimedia (pp. 223-232). ACM.

Cacioppo, J. T., & Petty, R. E. (1987). Stalking rudimentary processes of social influence: A psychophysiological approach. In Social influence: The Ontario Symposium (Vol. 5, pp. 41-74).

Chartrand, T. L., & Bargh, J. A. (1999). The chameleon effect: the perception–behavior link and social interaction. Journal of personality and social psychology, 76(6), 893.

Chitturi, R., Raghunathan, R., & Mahajan, V. (2008). Delight by design: The role of hedonic versus utilitarian benefits. Journal of Marketing, 72(3), 48-63.

Christodoulides, G., Jevons, C. and Blackshaw, P. (2011). The voice of the consumer speaks forcefully in brand identity: user-generated content forces smart marketers to listen. Journal of Advertising Research, Vol. 51, No. 1, pp. 101-111.

Dimberg, U. (1982). Facial reactions to facial expressions. Psychophysiology, 19(6), 643-647.

Druckman, D., & Bjork, R. A. (Eds.). (1994). Learning, remembering, believing: Enhancing human performance. National Academies Press.

Eckler, P., & Bolls, P. (2011). Spreading the virus: Emotional tone of viral advertising and its effect on forwarding intentions and attitudes. Journal of Interactive Advertising, 11(2), 1-11.

Edell, J. A. (1988). Nonverbal Effects in Ads: A Review and Synthesis. In Nonverbal Communication in Advertising. Eds Hecker, S; Stewart, D. New Yord, Lexingon Books, in press.

Edell, J. A., & Burke, M. C. (1987). The power of feelings in understanding advertising effects. Journal of Consumer research, 421-433.

Ekman, P. (1992). "An argument for basic emotions". Cognition and Emotion 6 (3): 169–200.

Ekman, P., Friesen, W. V., & Scherer, K. R. (1976). Body movement and voice pitch in deceptive interaction. Semiotica, 16(1), 23-28.

Ferrara, E., & Yang, Z. (2015). Measuring Emotional Contagion in Social Media. PloS one, 10(11), e0142390.

Gotthilf, G., 2010. 7 practical steps to managing a Facebook crisis. Blueglass, September 30, available at: www.blueglass.com/blog/7-practical-steps-to-managing-a-facebook-crisis/

Guadagno, R. E., Rempala, D. M., Murphy, S., Okdie, B. M. (2013). What makes a video go viral? An analysis of emotional contagion and Internet memes. Computers in Human Behavior, 29(6), 2312-2319.

Guillory, J., Spiegel, J., Drislane, M., Weiss, B., Donner, W., & Hancock, J. (2011). Upset now?: Emotion contagion in distributed groups. In Proc. CHI 2011, ACM Press (2011), 745-748.

Gulas, C. S., & Larsen J. E., 2012. Silence is Not Golden: Firm Response and Nonresponse to Consumer Correspondence. Services Marketing Quarterly 33(3), pp. 261-275.

Hancock, J. T., Gee, K., Ciaccio, K., & Lin, J. M. H. (2008). I'm sad you're sad: Emotional contagion in CMC. In Proc. CSCW 2008, ACM Press (2008), 295-298.

Hareli, S., & Rafaeli, A. (2008). Emotion cycles: On the social influence of emotion in organizations. Research in organizational behavior, 28, 35-59.

Hargie, O. (2010). Skilled interpersonal communication: Research, theory and practice. Routledge.

Hatfield, E., Cacioppo, J. T., & Rapson, R. L. (1992). Primitive emotional contagion. In R. L. Clark, & S. Margaret (Eds.), Emotion and social behavior, review of personality and social psychology, Vol. 14 (pp. 151-177). Thousand Oaks, CA: Sage.

Hatfield, E., Cacioppo, J. T., & Rapson, R. L. (1993a). Emotional contagion. Current Directions in Psychological Science, 2(3), 96-100.

Hatfield, E., Cacioppo, J. T., & Rapson, R. L. (1993b). Emotional contagion. Cambridge, UK: Cambridge University Press.

Hatfield, E., Cacioppo, J., & Rapson, R. L. (1994). Emotional contagion. New York: Cambridge University Press.

Heath, R., Brandt, D., & Nairn, A. (2006). Brand relationships: Strengthened by emotion, weakened by attention. JOURNAL OF ADVERTISING RESEARCH-NEW YORK-, 46(4), 410.

Heckman, R., & Guskey, A. (1998). The relationship between alumni and university: toward a theory of discretionary collaborative behavior. Journal of Marketing Theory and Practice, 97-112.

Hietanen, J. K., Surakka, V., & Linnankoski, I. (1998). Facial electromyographic responses to vocal affect expressions. Psychophysiology, 35(05), 530-536.

Izard, C. E., Bartlett, E. S., & Marshall, A. G. (1972). Patterns of emotions. Acad. Press.

Kelly, J. R., & Barsade, S. G. (2001). Mood and emotions in small groups and work teams. Organizational behavior and human decision processes, 86(1), 99-130.

Kim, J., & Gupta, P. (2012). Emotional expressions in online user reviews: How they influence consumers' product evaluations. Journal of Business Research, 65(7), 985-992.

Kramer, A. D., Guillory, J. E., & Hancock, J. T. (2014). Experimental evidence of massive-scale emotional contagion through social networks. Proceedings of the National Academy of Sciences, 111(24), 8788-8790.

Ladhari, R. (2007). The effect of consumption emotions on satisfaction and word-of-mouth communications. Psychology & Marketing, 24(12), 1085-1108.

Levy, D. A., & Nail, P. R. (1993). Contagion: A theoretical and empirical review and reconceptualization. Genetic, Social, and General Psychology Monographs.

Litvin, S. W., Goldsmith, R. E., & Pan, B. (2008). Electronic word-of-mouth in hospitality and tourism management. Tourism management, 29(3), 458-468.

Mittal, V., Kumar, P., & Tsiros, M. (1999). Attribute-level performance, satisfaction, and behavioral intentions over time: a consumption-system approach. The Journal of Marketing, 88-101.

Morrison, S., & Crane, F. G. (2007). Building the service brand by creating and managing an emotional brand experience. Journal of Brand Management, 14(5), 410-421.

Neumann, R., & Strack, F. (2000). "Mood contagion": the automatic transfer of mood between persons. Journal of personality and social psychology, 79(2), 211.

Noble, C. H., Noble, S. M., & Adjei, M. T. (2012). Let them talk! Managing primary and extended online brand communities for success. Business horizons, 55(5), 475-483.

Oliver, R. L. (1997). Satisfaction: a behavioral perspective on the consumer. McGraw-Hill series in marketing Show all parts in this series.

Peters, K., & Kashima, Y. (2007). From social talk to social action: shaping the social triad with emotion sharing. Journal of Personality and Social Psychology. 93(5), 780-97.

Plutchik, R. E., & Conte, H. R. (1997). Circumplex models of personality and emotions. American Psychological Association.

R Core Team. "R: A Language and Environment for Statistical Computing." R Foundation for Statistical Computing. Vienna, Austria, available at http://www.R-project.org, 2013.

Reber, A. S. (1995). The Penguin dictionary of psychology. Penguin Press.

Reynolds, K. E., & Beatty, S. E. (1999). Customer benefits and company consequences of customer-salesperson relationships in retailing. Journal of Retailing, 75(1), 11-32.

Russell, J. A. (1980). A circumplex model of affect. Journal of personality and social psychology, 39(6), 1161.

Ruth, J. A. (2001). Promoting a brand's emotion benefits: the influence of emotion categorization processes on consumer evaluations. Journal of Consumer Psychology, 11(2), 99-113.

Scarduzio, J. A., & Tracy, S. J. (2015). Sensegiving and Sensebreaking via Emotion Cycles and Emotional Buffering How Collective Communication Creates Order in the Courtroom. Management Communication Quarterly, 0893318915581647.

Schachter, S. (1959). The psychology of affiliation. Standford University Press.

Strapparava, C., & Valitutti, A. (2004, May). WordNet Affect: an Affective Extension of WordNet. In LREC (Vol. 4, pp. 1083-1086).

Swan, J. E., & Oliver, R. L. (1989). Postpurchase communications by consumers. Journal of Retailing.

Teixeira, T. S., Wedel, M., & Pieters, R. (2010). Moment-to-moment optimal branding in TV commercials: Preventing avoidance by pulsing. Marketing Science, 29(5), 783-804.

Tellegen, A. (1985). Structures of mood and personality and their relevance to assessing anxiety, with an emphasis on self-report.

Thogersen, J., Juhl, J. J. & Poulsen C. S: (2009). Complaining: A function of attitude, personality, and situation. Psychology & Marketing, 26(8), 760–777.

Thompson, C. J., Rindfleisch, A., & Arsel, Z. (2006). Emotional branding and the strategic value of the doppelgänger brand image. Journal of Marketing, 70(1), 50-64.

Totterdell, P. (2000). Catching moods and hitting runs: mood linkage and subjective performance in professional sport teams. Journal of Applied Psychology, 85(6), 848.

Tsai, S. P. (2005). Utility, cultural symbolism and emotion: a comprehensive model of brand purchase value. International journal of Research in Marketing, 22(3), 277-291.

Verhagen, T., Nauta, A., & Feldberg, F. (2013). Negative online word-of-mouth: Behavioral indicator or emotional release?. Computers in Human Behavior, 29(4), 1430-1440.

Westbrook, R. A. (1987). Product/consumption-based affective responses and postpurchase processes. Journal of marketing research, 258-270.

Zaugg, A. & Jaggi, N. (2006). The impact of customer loyalty on complaining behavior. IADIS International Conference.

Zajonc, R. B. (1980). Feeling and thinking: Preferences need no inferences. American psychologist, 35(2), 151.